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A SEARCH FOR UNDERSTANDING: ANALYSIS OF HUMAN PERFORMANCE ON TARGET ACQUISITION AND SEARCH TASKS USING EYETRACKER DATA

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PREFACE

This paper was prepared for Thomas Hafer, Deputy Director Advanced Systems Technology Office, ARPA, under an IDA task on Analysis and Model Development. Additional technical cognizance and direction have been provided by Eugene Patrick and John Brand, U.S. Army Research Laboratory, Weapons Technology Directorate. The authors are grateful to Walter Lawson for many useful comments.

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SUMMARY

A. OVERVIEW

This paper reviews a proposed mathematical framework for the human target acquisition and search model, the "neoclassical model," and applies this model to a recent human perception experiment conducted by the U.S. Army Night Vision and Electronic Sensors Directorate (NVESD, informally known as the Night Vision Laboratory or NVL). This experiment used an eye-tracking device so that the motion of the observer's gaze in an image could be monitored as well as his detection performance. The experiment and model development are part of efforts to improve target acquisition and search models and provide a closer alignment of the overall performance models with modern understanding of the human visual and cognitive systems.

The goal is to establish a relationship between human performance, background clutter, and target signatures that will apply to all targets, including camouflaged or low-observable targets, and for both aided and unaided search. This paper provides the experimental evidence to support the underlying assumptions of the neoclassical model and gives the basis for extrapolation of the model to a wide range of applications. The detailed analysis provided in this paper is important primarily because it develops our basic understanding of the issues of search and target detection across the board. Combined with the parallel work reported in O'Kane (1995), Do-Duc (1995), Silk (1995), and Cartier and Hsu (1995a and b), considerable progress has been made in understanding search. Together, this "search for understanding" will lead to improvements in the target acquisition and search models used in the Army and will provide the basis for both the camouflage designs and sensor and signal processing approaches to defeat camouflage.

The results analyzed here show that the search and detection in the 4B experiment can be adequately described by a limiting case of the neoclassical model that is completely determined by three parameters:

(1) The mean time-on-target required for detection. This is the average amount of time spent by the observer examining the target directly required to declare a point of interest to be a target. This is a measure of the difficulty in determining the character of a target and may be longer for deceptive targets.

(2) The fraction of time spent on the target. The observer's time is divided between the target of interest, other distracting target candidates, and general wandering in the field of view. The overall fraction of time spent on the target is a measure of the overall attractiveness of the target and its surroundings.

These two parameters are sufficient to provide a good description of the distribution of target detection times from the moment of first encounter with the target.

(3) The average length of a visit to a target. This time scale, in conjunction with the fraction of time spent on the target, determines the length of visit and the separation between visits and, hence, the overall structure of the search and the mean time to the first encounter with the target.

The success of the neoclassical framework for describing detection and search with these parameters strongly suggests that future work should be concentrated on accurate predictions of these quantities.

B. DATA ANALYSIS

The neoclassical model uses a memory-less Markov approach to modeling the search and detection processes. The observer is represented as moving his gaze from point to point in the image, the transitions between one point and another being determined by the attractiveness of that area of the image. This target attractiveness is presumed to be calculated or estimated from a detailed understanding of the target signature and background, combined with the models of human vision. A sufficiently robust target, background, and vision model should provide all of the parameters by the neoclassical model for describing the search; if not available, these parameters can be described phenomenologically by correlating them with known target and background characteristics.

The observer is described as "examining" specific points of interest, or target candidates, or "wandering" at random in the image. The observer may visit a particular target more than once; detection is modeled by accumulating the total length of time spent on these visits, the time-on-target. The neoclassical model assumes that the probability of detection is an exponential function of the time-on-target. The detection rate may also be computed from the target metrics and vision models or may be represented empirically.

Combining the detection rate parameter with the search parameters gives a description of the overall probability of detection that is a combination of several exponentials. The number of different exponential terms depends on how detailed a description of the search process is used. In the most general case elaborated here, three exponentials are

predicted; however, a special case requires only two exponents. The classical search and detection model currently used by the Army is represented by a single-exponential, two-parameter model. The predicted probability of detection is:

$$P_D(t) = P_\infty\left(1 - e^{-t/\tau}\right) \quad . \tag{S-1}$$

P_∞ is the fraction of an ensemble of observers that will eventually detect the target. For each observer who will see the target, the time constant, τ, describes the detection rate. P_∞ and τ are typically estimated by straightforward heuristic extensions of the static performance model with τ often taken as $\tau = 3.4/P_\infty$ seconds. The effects of competing targets and clutter are included in an ad hoc fashion based on field experience.

The classical model is simple and simplicity is an important attribute of any model used as a component of overall systems modeling. However, the details of human search performance experiments are highly complex and cannot always be satisfactorily represented by Eq. (S-1). In addition, the two parameters of the classical model, while they provide adequate guidelines to performance, do not allow for detailed and quantitative description of clutter backgrounds; in particular, they may not address the problems associated with low observable targets or severe clutter. It is therefore desirable to place the classical model into a more general mathematical framework. This will provide a better understanding of the limitations of the classical approach as well as giving a more fundamental method for estimating the crucial parameters of the model. The neoclassical model provides a general framework that permits the addressing of a broader domain of search applications without violating the need for simplicity.

There were two primary goals in the analysis of human performance data given here. The first goal was to test the validity of the underlying assumptions of the neoclassical model. For example, the Markov framework used implies that the observer may visit the target several times before declaring it to be a target and may revisit it after detection. This qualitative feature is required for the neoclassical model and was not addressed in the classical formulation. The second goal was to compare the predictions of the neoclassical model and the classical model with the experimental data on a quantitative basis. To pursue the second goal completely, the search and detection parameters used in the neoclassical framework would need to be predicted for the images analyzed by the target signature metrics, background characterization models, and human vision representations. Since these predictions were not available during the analysis, only consistency with the neoclassical predictions could be checked.

C. CONCLUSIONS AND RECOMMENDATIONS

The conclusions that can be confirmed by the human perception experiment are enumerated as follows.

- The pattern of eye motions confirms the "random" nature of the search assumed.
- The measured eye locations can be divided relatively easily into wandering and examining states.
- There are multiple visits to the target both before and after detection.
- A detection model that is exponential in the time-on-target is appropriate.
- The process of examining the target is consistent with a Markov model.

The separations between visits are a probe of the details of the Markov process. For the full neoclassical model, the gap distribution should be described as the sum of two exponentials, reducing to a single exponential in the special case.

- A single exponent is a reasonable fit for the visit separation data.

The probability of detection is, of course, the prediction of primary interest in any search and detection model. For the two-exponent limiting case, the neoclassical fits use the exponents and amplitudes calculated from the search model parameters as extracted from the data and the time-on-target to detect and predict the actual clock time to detect.

- The neoclassical model predictions are consistent with the number of detections as a function of either total clock time or shifted time.
- Qualitative features of the neoclassical model are exhibited.

All of the above results support the neoclassical model framework and its assumptions. From a practical point of view they mean that the search and detection can be adequately described by a limiting case of the neoclassical model that is completely determined by the three parameters discussed above:

(1) The mean time-on-target required for detection.

(2) The fraction of time spent on the target.

(3) The average length of a visit to a target.

The remaining parameters of the full neoclassical model cannot be reliably determined by examination of the detection data in the 4B experiment and are essentially irrelevant for single target detection (they may be more relevant for multi-target correlation).

There are necessarily some caveats:

- Preliminary analysis indicates that the time to the first visit is not well described by the neoclassical search model or the classical model.
- The overall fit to the data with a single exponent, while not as good as the neoclassical two-exponent fits, is acceptable. For targets with relatively large values of P_∞ but not for lower P_∞ targets, the value of the exponent is well represented by the classical approximation $\tau = 3.4/P_\infty$.
- The duration of the detection visit is longer than the typical pre-detection visit; the most obvious explanation being extra cognitive processing upon making the decision. This may have some consequences for multi-target search.
- The pre-detection and post-detection distributions of visit durations and separations between visits appear to differ, implying learning. This may have some consequences for multi-target search.

There are a number of issues that require further study within the experiment and which may suggest the need for further experimental efforts:

(1) The conclusion that the two-exponent limiting case of the neoclassical model is sufficient was made on the basis of examining the visit and detection data rather than from the details of the search itself. Further analysis may be able to demonstrate this conclusion directly.

(2) The parameters used in the description of the data were extracted from the data rather than being predicted *a priori* from a target signature and vision model. Further analysis may be able to correlate these parameters with observable features of the image, if not obtainable from a computational vision model.

(3) Only the most salient point of interest in each image was explicitly considered in the current analysis. Further supporting information about the nature of the search can be obtained by extending the analysis to all the points of interest and by considering multi-target correlations.

(4) The deviations from the strict classical prediction of overall time-to-detect in this experiment lay primarily in the low P_∞ targets. These targets are the most difficult to study since fewer observers detect them. A more detailed analysis may elucidate the search and detection parameters of these targets.

(5) The targets used were relatively easy to detect. The mean number of visits required to detect most of the targets was about 1.5. More difficult targets would provide a clearer test of the neoclassical model.

(6) Since the neoclassical model fits depend entirely on only three parameters, the final recommendation is that a concerted effort be made to predict them and their dependence on target signatures and backgrounds in greater detail.

Although, as in any experiment with human observers, the cogency of these conclusions may be limited by the size of the data base, the overall conclusion is that the foundations of the neoclassical search model are validated by this experiment.

I. REVIEW OF NEOCLASSICAL SEARCH MODEL

A. INTRODUCTION

This paper provides an analysis of recent human field-of-view search performance experiments performed by the Night Vision Laboratory. The experiments used trained subjects in examining simulated infrared imagery and employed in the 4B experiment[1] an eye-tracker to enable monitoring the subjects' search process. The data will be analyzed in the context of a recently proposed extension of the standard or "classical" human search model, called "the neoclassical model." The purpose of the analysis is to determine whether or not the assumptions underlying the neoclassical model and its detailed conclusions can be verified in actual experimental data.[2]

The proposed model is termed "neoclassical" because it is intended to be only a small departure from the classical search model. [An excellent review of the standard model is given in Howe (1993).] The neoclassical model incorporates a broad mathematical framework that addresses complex modeling issues without becoming so cumbersome that it cannot be used in large-scale modeling simulations such as Janus [Parish and Kellner (1992)]. The framework was developed as part of the U.S. Army Target Acquisition Model Improvement Program (TAMIP). As a part of this program, new metrics have been devised for clutter, target signatures, and target attractiveness[3] [O'Kane et al. (1993), D'Agostino et al. (1993), Kowalczyk et al. (1993), Witus (1993), Doll (1993)]. The target attractiveness metrics use detailed computational vision models of the human visual system, as well as target and background metrics to provide a measure of a

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1 B. O'Kane (1995) describes the complete series of 4A, 4B, and 4C experiments; H. Do-Duc (1995) describes the eye-tracker and its use in experiment 4B.

2 Other aspects of the NVL experiments are analyzed elsewhere; for example, false alarm performance is discussed in Silk (1995) and detailed Monte Carlo simulations are described in Cartier et al. (1994).

3 Target attractiveness is a measure of the propensity of a target to attract the eye of the observer and may, in principle, be distinguished from target signatures that are used to measure detection or recognition performance once the target is considered by the observer. The distinction will only be valuable when target attractiveness metrics have been separately validated. In the interim, any target signature metric can be considered as a candidate for measuring target attractiveness.

particular target's strength in the search process. The neoclassical connects the target attractiveness models to the search and target acquisition modeling domains.

The classical field-of-view search model is represented by a single-exponential, two-parameter model. The predicted probability of detection is:

$$P_D(t) = P_\infty \left(1 - e^{-t/\tau} \right) \quad . \tag{I-1}$$

P_∞ is the fraction of an ensemble of observers that will eventually detect the target [but see Rotman (1989) for comments on P_∞]. The time constant, τ, describes the detection rate for each observer who will see the target. P_∞ and τ are typically estimated by straightforward heuristic extensions of the static performance model. The effects of competing targets and clutter are included in an ad hoc fashion based on field experience.

The classical model is simple and simplicity is an important attribute of any model used as a component of overall systems modeling. However, the details of human search performance experiments are highly complex and cannot always be satisfactorily represented by Eq. (I-1). In addition, the two parameters of the classical model, while they provide adequate guidelines to performance, do not allow for detailed and quantitative description of clutter backgrounds; in particular, they may not address the problems associated with low observable targets or severe clutter. It is therefore desirable to place the classical model into a more general mathematical framework. This will provide a better understanding of the limitations of the classical approach as well as giving a more fundamental method for estimating the crucial parameters of the model. The neoclassical model provides a general framework that permits the addressing of a broader domain of search applications without violating the need for simplicity. For examples of data analysis of experiments exhibiting complex detection versus time curves see Blecha et al. (1991), Nicoll (1992), Rotman et al. (1991), and Cartier et al. (1994, 1995a and b). A summary of this paper also appears in Nicoll and Hsu (1995).

B. NEOCLASSICAL APPROACH

The search process is assumed to be represented by a series of partly random eye movements, or "saccades," separating different eye positions, or fixations,[4] on the image plane (see Fig. I-1). The sequences are divided into two classes:

- "Random" wandering paths, and
- Examination of points of interest (either targets or clutter objects).

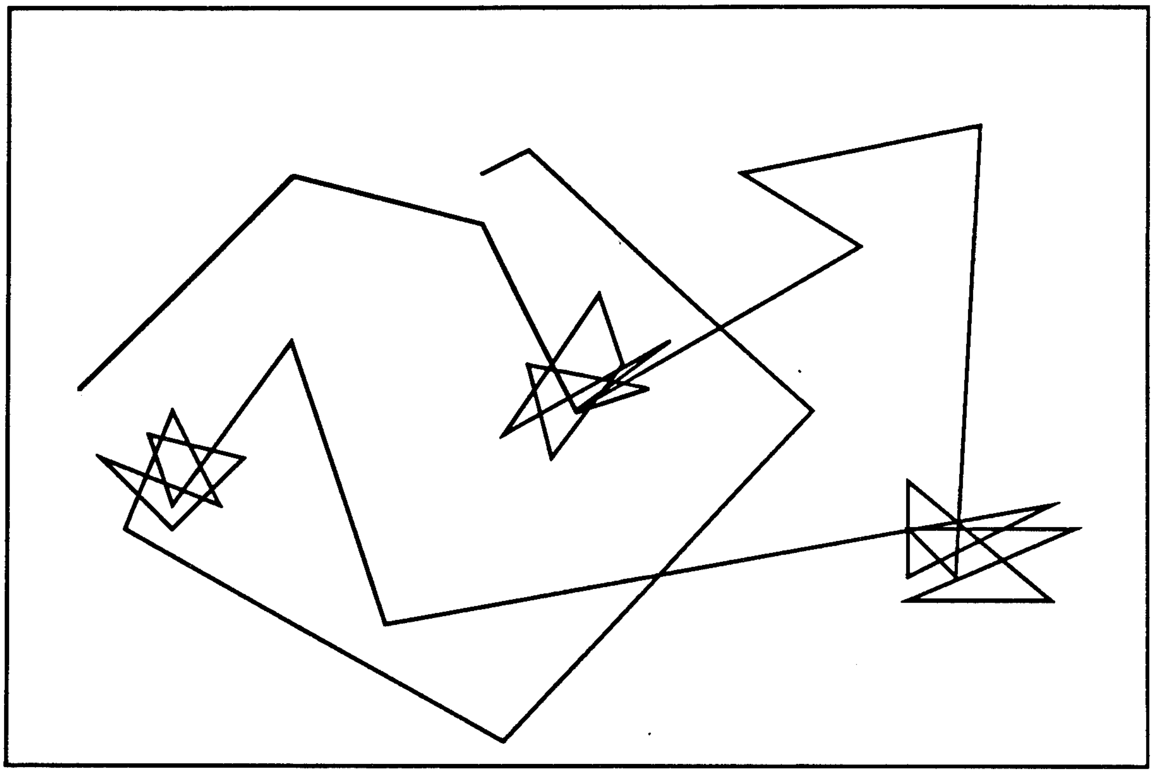

Figure I-1. Sketch of Eye Movements In Field of View Search

4 Yarbus (1967) asserts that the "human eye can only be in one of two states: in a state of fixation or in a state of changing the point of fixation." Thus, the entire pattern of the eye motions across the image can be described as a sequence of fixations separated by motions. Some authors would describe a sequence of small eye movements near a single point as a single long fixation rather than a sequence of fixations around a single point. Even while fixated near a single point, the eyes are subject to drift (while keeping the object in the foveal region), tremor (a high-frequency low-amplitude motion) and small involuntary saccades (if the duration of the fixation near the point exceeds 0.3–0.5 seconds or the object of interest drifts out of the foveal region).

It is assumed that the observers dwell on each point of interest for a substantial amount of time and then return to wandering or jump directly into another detailed study of a different point of interest.[5] It is the task of any search model to develop a mathematical description of the search process and to combine that description of eye movements with a model of the process of declaring a point of interest to be a target.

When we apply existing mathematical models of visual and cognitive process associated with search and detection, they can easily become too complicated and detailed to be validated or applied in practice. In the neoclassical model, the emphasis is on reducing the complexity of the formulation. A reasonable starting point is the Markov process [evidence that search is a Markov process is discussed in Harris (1993)]. A Markov process consists of a number of states with specified transitions between the states. In the context of search, one could assign a separate state to each possible fixation point in the field of view. The transitions would then correspond to the probabilities that the observer moves his gaze from one point to another during search.

The probability of detection predicted by a Markov process model is a linear combination of exponential terms (one for each state) rather than the single exponential in the classical model. This approach can be useful if the number of states used is small. Using a separate state for each point in the scene is not practical because the number of states is too large. On the other hand, the classical model is a two-state Markov model: the first state represents a continuing search, while the second state represents detecting the target.[6] This does not provide enough flexibility to describe the effects of multiple targets and clutter. The goal of this paper is to strike a balance between these extremes, retaining a

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5 These two classes are easy to determine *a postiori* from the eye-tracking data. There are specific localized regions in the image at which the observers spend a sizable fraction of the time with relatively small and slower eye movements. These areas define the points of interest in the image. The paths connecting these areas appear in some cases to represent direct jumps from one of these points of interest to another, but in other cases appear to be less well-defined sequences of eye positions or "wandering." Although the points of interest visited by different observers may vary slightly, there is a clear ensemble consensus on the points of interest. From a mathematical point of view, the wandering state in the neoclassical model can be viewed as simply representing that time which is neither spent in detailed examination of points of interest nor is clearly part of a single rapid saccade jump between points of interest. Robust target and background metric characterizations should be able to determine the points of interest from the image itself *a priori*. The determination of points of interest from target and clutter metrics is an area of active interest under TAMIP.

6 There are, in fact, two exponents in this Markov description of the classical model; the second exponent is zero and describes the fact that the sum of the probability of detecting and not-detecting the target is unity.

sufficient number of states to accurately describe the search without unnecessarily complicating the results.

The neoclassical model assigns a separate state to each target or target-like clutter point; these are described in terms of the target attractiveness or target signature metrics. Assigning a state to every target candidate is necessary if the effects of competing targets and clutter are to be handled. In general, this would lead to as many exponents as target-candidates and would be too unwieldy for most applications. However, by representing the large number of state-to-state transition rates by a few average transition rates, we can reduce the number of exponents to a small number. The states of the neoclassical model are shown in Fig. I-2.

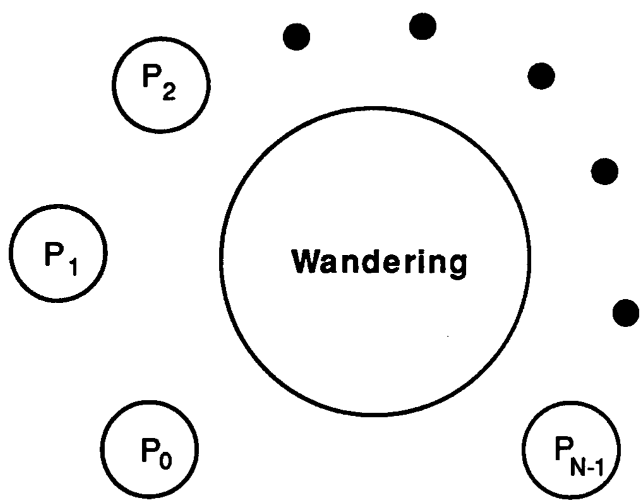

Figure I-2. Markov States for the Neoclassical Model

All of the non-point-of-interest eye locations are combined into a single Markov state called "wandering"; separate states are maintained for each of the points of interest (POI). Only average transition rates are specified (rather than individual rates between each of the Markov states). The neoclassical model uses a simpler approximation that specifies the minimum number of rates to describe the system.

The rates chosen govern the average transition rate between the wandering states and the POIs and between the POIs:

W = average rate of the observer leaving a POI to wander,

S_i = average rate of the observer entering the ith POI from wandering, and

J_i = average rate of entering the ith POI from another POI.

Thus, each POI is described by two parameters governing its "cueing strength" or "desirability": S_i and J_i specify how often the eye will be drawn to the ith POI from the wandering state or another POI, respectively; they are proportional to the probability, P_{cue}, of the eye's being cued to the target given that the observer is wandering or examining a competing POI. These rates are all, in principle, experimentally measurable in human performance eye-tracking experiments and have a direct physical meaning, as well as being calculable, in principle, from the signature models under development. It is convenient to define total transition rates $S = \Sigma S_i$ and $J = \Sigma J_i$. A special case of the neoclassical model is the case of $J_i = S_i$. In this case, the model does not distinguish wandering from examining a distracter: there is only examining the target and doing "something else." This case is mathematically somewhat simpler but less flexible; it is equivalent to a smoke obscuration model [see Rotman et al. (1991) and Nicoll and Silk (1991, 1993)].

The parameters given describe the search process itself but do not describe detection. As an approximation, the neoclassical model assumes that the detection of a target does not directly affect the search process.[7] One can imagine that the search process is carried out under the direction of one master search program that occasionally issues a detection report and then continues the search. The basic detection mechanism is assumed to be exponential. This is used not only because it is simple and fits naturally into the Markov representation of the search, but also because it can be used to generate other models. The exponential detection model assumes that the probability of detection is determined by the time actually spent observing the target rather than the total clock time of the search. Consider a specific target (the 0th); the time spent fixated on that target, $T_0(t)$, is a well-defined function of each particular search path. The probability of detection of the 0th target is therefore:[8]

$$P_D(t) = 1 - e^{-\alpha_0 T_0(t)} , \tag{I-2}$$

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7 This is clearly an approximation made for simplicity. As this paper will show, there are clearly demonstrable changes in the search behavior after declaration of one point of interest as a target. However, assuming this independence allows a straightforward extension to multitarget search and detection [see Nicoll (1994) for a discussion of the multitarget case and nonstationary Markov extension of the neoclassical model to more correctly represent the learning effects].

8 Note that this represents the distribution of detection times. Individual detections can occur either very rapidly or more slowly. In fact, the most probable detection time for an exponential distribution is zero, while the mean detection time and standard deviation are given by $1/\alpha_0$.

where α_0 is the detection rate while the observer is cued to the target; it is proportional to $P_{det|cue}$. Since the particular search path taken by the observer is not known, we couple the expected value of the probability of detection by averaging over all search paths:

$$P_D(t) \quad = \quad \langle 1 - e^{-\alpha_0 T_0(t)} \rangle \ , \tag{I-3}$$

where the < ... > averages over the Markov process controlling the search [for a mathematical description of path integrals, see Chang et al. (1992)]. The difference between the neoclassical and classical models arises in the computation of this average value; the neoclassical approximations lead to a P_D that is the sum of three exponentials:[9]

$$P_D(\alpha_0, t) \ = \ \sum_{i=1}^{3} e_i \, (1 - e^{-\lambda_i t}) \ . \tag{I-4}$$

The eigenvalues λ_i are determined from the Markov process and are functions of the overall search parameters W, S, and J, and the target-specific parameters S_0, J_0, and the detection rate α_0. The amplitudes of these exponentials are determined by search and target parameters and the initial conditions. The initial conditions of the search determine the probability that the observer was initially wandering over the scene and the probability that the observer was fixated on the target of interest. Ideally, an analysis of the data from an experiment would provide values of the eigenvalues, initial conditions, and rates.

The relationship of the detection processes at each POI and the total search process is analogous to a time-sharing system. The search process governs the visits of the observer to each POI; it represents the scheduling algorithm of the time-sharing system. While an observer is at a particular POI the detection process for that target candidate (the POI's detection "program") is permitted to run. In the neoclassical model, for each POI considered separately, the other POIs collapse into a single distracter state and act as a load on the system, slowing down the performance. For each computation of the probability of detection, the many states of the problem are effectively reduced to three, as illustrated in Fig. I-3. Each object in the scene obeys an equation of the same form, permitting the simple description of multiple targets and false alarms in the same formalism.

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9 The number of exponents in any Markov description of search depends on the number of Markov states and the degree of generality of the transitions allowed between states. In general, one would expect N exponents for a system of N states. This is reduced to 3 in the neoclassical framework by making simplifications in the transition rates: namely, replacing individual transition rates between points in the image with average rates. Setting $J_i = S_i$ is another simplification of the transition rates that reduces the exponents to two.

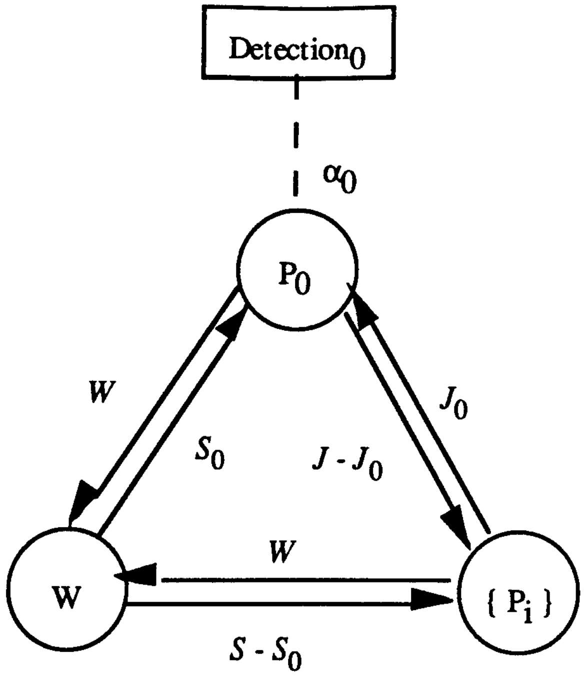

Figure I-3. Effective Processes as Seen by Each Detection Process

As noted above, if $J_i = S_i$, then the other points of interest and wandering state may be combined insofar as the chosen point of interest is concerned. The three-exponent model collapses to two. This special case of the neoclassical model has a smaller number of parameters to be determined and less dependence on the precise initial conditions. The data analysis of this paper will endeavor to determine whether or not the data support $J_i = S_i$.

The value of the exponents and the amplitude coefficients depend on the relative attractiveness of the target of interest and the competing targets and clutter. For searches with long overall search times (> 10 seconds), one eigenvalue is much smaller than the others and dominates P_D for long times; the three-exponent model reduces to the single-exponent, classical model with a time constant determined by the competing targets and clutter. The remaining terms act as small corrections for short times. Thus, the important difference between the neoclassical and classical models is not the difference between one exponent and three exponents; there is nothing magical about three exponents. Rather, the neoclassical model provides the modeler with a systematic method for computing search times from target and clutter metrics describing the scene. For further mathematical details, the reader is referred to the more extended development in Nicoll (1994). Results from the earlier work will be quoted without detailed derivation.

For future reference, the exponents or eigenvalues are the solution of a cubic equation:

$$\lambda(\lambda-(W+S))(\lambda-(W+J+\alpha))-\alpha(S_0W+J_0S-J_0\lambda)=0 \quad . \qquad \text{(I-5)}$$

The coefficients contributing to the probability of detection in Eq. (I-4) are given by:

$$e_i = \frac{\alpha_0\left[\frac{S_0W+J_0S}{\lambda_i} - S_0w(0) - J_0p(0) + p_0(0)\,(\lambda_i - R)\right]}{(\lambda_i - \lambda_j)(\lambda_i - \lambda_k)} \quad , \qquad \text{(I-6)}$$

where in Eq. (I-6) i, j, k = 1, 2, 3 and permutations and $R = W + S$. All of the results of Nicoll (1994) are obtained by the study of the consequences of Eqs. (I-4), (I-5), and (I-6).

II. OVERALL PHENOMENOLOGY

The eye-tracking data analyzed was taken from the NVL 4B perception experiment. A number of simulated infrared images were shown to 12 or 13 observers. Eye-tracker location data was reported at a 30-Hz rate.

Some smoothing of the eye-tracker data is required before an analysis can begin. The neoclassical model ideally is concerned with cognitive states, examining targets, and wandering; on the other hand, the eye-tracker provides only the location of the eye (and is subject to errors and biases in that location) and does not provide direct access to the cognitive state. It is assumed in the current analysis that an observer can only be "examining" a target when he is fixated on the target and that, when he dwells on a target (fixates near the target location for an extended time), he is examining the target in the cognitive sense.

With respect to the eye-tracker data, there are obvious points of interest as suggested by Fig. I-1 associated with targets and target candidates. Boxes were drawn around the points of interest and the observer was defined as visiting (examining) a target if the eye-tracker location fell within the box. Individual boxes for each observer-target combination had to be constructed since the centroids of the measured eye positions varied from observer to observer (either due to eye-tracker bias or individual variations in the most comfortable fixation point). The data were then smoothed to remove two artifacts:

1. False visits. If the observer is saccading from one part of the image to another, the eye-tracker will plot several points along the saccade path. These may lie in the target box, but do not represent genuine visits to the target. These false visits were removed by demanding that any visit to a target (presumed examination) had to last at least some fixed number of eye-tracker counts. The eye-tracker operated at 30 Hz so that 3 points in a box would represent 0.1 second. A variety of minimum visit times were explored. For this report, visits shorter than 0.167 seconds were eliminated.

2. False exits. The eye-tracker traces sometimes show an observer fixated within a target box and then briefly looping out of and back into the box. These could be the result of genuine "wandering" search paths or a poor choice of the box, eye-tracker error, or a twitch of the observer. To eliminate these false exits, a threshold was applied to the size of the gap between visits. A number of gap

thresholds have been examined; for this paper, gaps of size 0.2 seconds or less were ignored and merged with the surrounding visits.

Other methods of filtering the data (such as velocity filtering) have also been considered.[1] To be able to study both the search and detection characteristics of the experiments, the analysis of this paper is restricted to those points of interest that were designated as targets by at least 5 observers. This limitation effectively reduced all of the 11 images studied to the single target-in-clutter case since there was no image for which two objects were designated as a target by 5 (possibly different) observers. The images did, however, contain other points of interest that were examined in detail by the observers.

The observers who did not detect the target were eliminated from the experimental database. Of the possible 139 observer-target pairs, 25 were eliminated for non-detection, leaving 114. In addition, one observer apparently detected the target without ever having been fixated on the target. That is, the observer indicated that he detected a target by pressing a button on the computer mouse, but the eye-tracking data do not show that he ever had the target within the foveal region. This has a number of possible explanations: (1) the target was detected in peripheral vision; (2) there was eye-tracker error or poor definition of the target box used in the analysis; or (3) the observer was anticipating his detection decision. An additional 12 observer-pairs were eliminated because the observer, although he had visited the target at one time, apparently detected or decided to declare detection of the target between visits to the target. These processes require further elucidation, but for simplicity the data were eliminated from portions of the analysis, leaving 101 observer target combinations for which all the analysis can be done.

In some cases the data base does not have to be reduced to this degree. For example, the statistics of the search itself do not require that the observer detect the target. For search statistics, such as visit length and visit separation and time to the first visit, detection is irrelevant. For these parameters the full data base can be employed. Whenever

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1 I.e., the precise method of smoothing employed morphological filters to close gaps in visits and open false visits. Morphological filters with different length kernels were used to vary the size of gaps and visits filtered out. A related data analysis issue is the question of time spent performing a rapid saccade. It is these saccades that induce the false visits to targets. There is evidence [Burr et al. (1994)] that the visual system is shut down during such saccades. This may imply that, from the perspective of the Markov search process using only cognitive states, this time is "off the clock" and should be removed from the eye-tracking experiments in order to more clearly analyze the search process. Of course, this delay time is real and has to be accounted for in the total time to detection. The use of additional Markov states to represent these physical delays is discussed in Nicoll (1994).

the results differ between the full and restricted database, it will be so noted. The data base used will be indicated when it is not clear from the context.

Table II-1 provides some summary data for the targets averaged over observers. The column labeled p_{eq} represents the equilibrium probability and gives the fraction of time spent examining the target before detection; two different values are given. The first is defined by $p_{eq} = T_v/(Ts + Tv)$ where T_v and T_s are the mean visit length and separation as given in the table. Since the mean visit length and separation before detection can only be calculated by using data from those observers who take at least two visits before detection and 2/3 of the observers detect the target on the first visit, these values are averages over approximately 1/3 of the data. The statistical error of this method is given in parentheses; some of the observers who contribute to this average do not detect the target. The second value of p_{eq} (in square brackets) is determined by demanding that:

$$< t_d > = < t_1 > + \frac{1}{\alpha_0 \, p_{eq}} \quad . \tag{II-1}$$

Eq. (II-1) holds for a search governed by any Markov process, not just the neoclassical model. The value of α_0 is estimated from the mean time on target to detect, $<T_d>$: $\alpha_0 = 1/<T_d>$. This method of estimating p_{eq} uses all of the data but has the disadvantage of using the detection data to estimate a search parameter. Note that the values are seldom in agreement even if the statistical uncertainty of the first approach is considered. This is a primary source of uncertainty in the analysis since the value of an important parameter of the search cannot be determined with great confidence.

T_d is the mean time on target for detection (how much time was spent examining the target before detection) and t_d is the elapsed clock time until detection. The mean time to the first visit was computed for those observers who do not start examining the target. Note that all the targets except for targets 1, 4, and 5 have very high values of P_∞, defined as the fraction of observers that detect the target.

The background scenes for targets 2, 3, 4, 7, 8, 9, and 10 were essentially the same, differing by time of day and minor perspective changes; targets 5 and 11 used images of another location with a somewhat larger change of perspective and time of day; targets 1 and 6 used distinct locations.

Table II-1. Summary Data for Entire Database

Image (Target No.)	P_∞	p_{eq} (error)	T_d	Time to *n* 1st Visit	t_d (secs)	Mean Gap	Mean Visit
a4130 (1)	0.5	0.44 [0.49] (0.12)	5	7.4	18.0	1.0	0.79
a7010 (2)	0.92	0.44 [0.87] (0.07)	2.5	1.3	4.1	1.5	1.2
a7110 (3)	1	0.58 [0.86] (0.17)	2.3	1.2	3.1	0.84	1.2
a8106 (4)	0.42	0.26 [0.51] (0.13)	3.8	2.8	9.5	2.1	0.74
a9104 (5)	0.62	0.43 [0.52] (0.6)	4.3	1.7	9.9	1.6	1.2
d4019 (6)	0.85	0.39 [0.71] (1.0)	1.6	2.9	5.5	1.6	1.0
d7009 (7)	1	0.35 [0.67] (0.16)	1.4	1	3.0	1.0	0.57
d7109 (8)	0.92	0.48 [0.92] (0.14)	1.1	1.2	2.9	1.4	1.3
d8007 (9)	0.85	0.67 [0.85] (0.11)	2.3	0.56	3	0.92	1.8
d8107 (10)	1	0.65 [0.92] (0.18)	2.1	0.66	3.1	0.77	1.4
d9103 (11)	0.92	0.61 [93] (0.15)	2.1	0.63	2.9	1.1	1.7

Figure II-1 shows the time-on-target to detection and total detection time as a function of the values of P_∞. Note that the values associated with the larger P_∞ values are relatively tightly bunched and that for the lower P_∞ targets, the times are much larger and more diverse. Figure II-2 compares the total detection time with the classical time constant approximated as

$$\tau_{classical} = 3.4/P_\infty \quad . \tag{II-2}$$

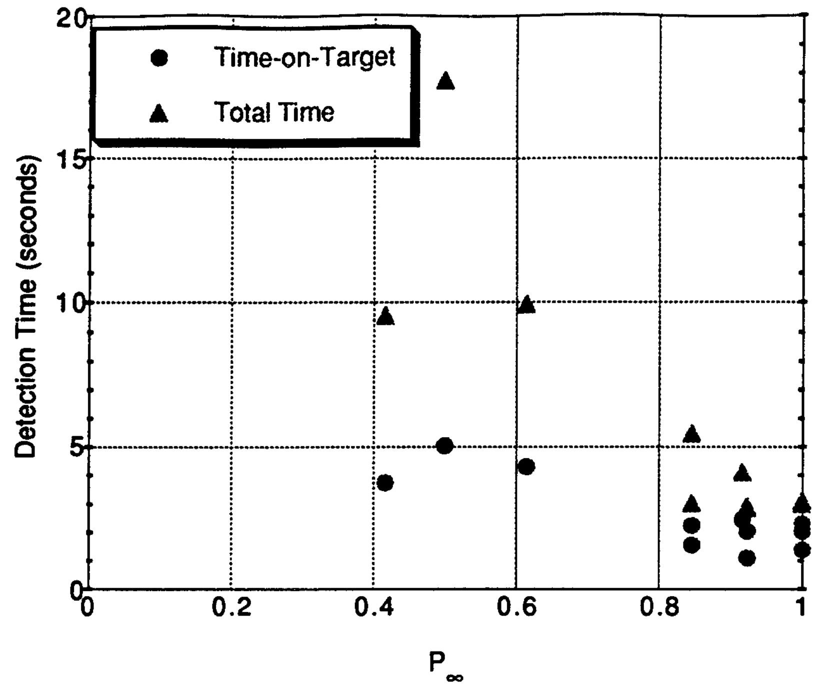

Figure II-1. Time-on-Target and Total Detection Time vs. P∞

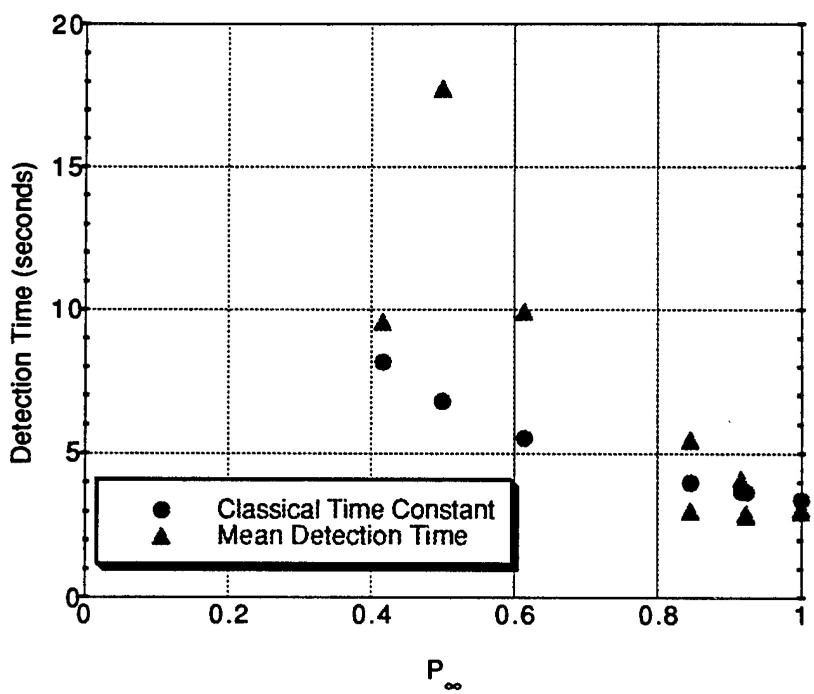

Figure II-2. Measured and Classical Predicted Detection Time vs. P∞

Note that there is reasonable agreement between the classical estimate and the measured mean time to detect for the high P_∞ objects with larger discrepancies for two of the lower P_∞ targets. Thus, the neoclassical model's additional mathematical apparatus is likely to be needed only for the less conspicuous targets. Unfortunately, these are precisely the targets for which fewer data are available since fewer observers detected them. This represents another limitation of the data analysis that can be undertaken using the 4B experiment; the experimental data from the higher P_∞ targets may, however, be used to validate the underlying assumptions of the neoclassical approach.

The lower P_∞ targets (1, 4, and 5) have other properties that separate them from the other targets. Figure II-3 shows the mean number of visits before detection plotted as a function of P_∞. While the high P_∞ targets are clustered around 1.5 visits, the other targets require distinctly more visits and have a wide variation. The figure also shows the implied value of the rate constant of the neoclassical model, $R = W + S$, assuming for this analysis that $J = S$. Note that the rate constant does not depend on the value of P_∞ but is about 2 sec^{-1} for all of the targets. If all the targets were part of the same image, then the neoclassical model would require that R be the same for all the targets since it is a summary measure of the search times in the image; since 7 of the 11 target scenes use essentially the same background the result is not surprising. Even for the 4 remaining images, the value of R does not seem to vary significantly. The fact that R does not depend on the image enables the pooling of the targets from different images without disrupting the search model. The differences in the targets appear to lie primarily in the different value of α for each of the targets, $\alpha = 1/\langle T_d \rangle$.

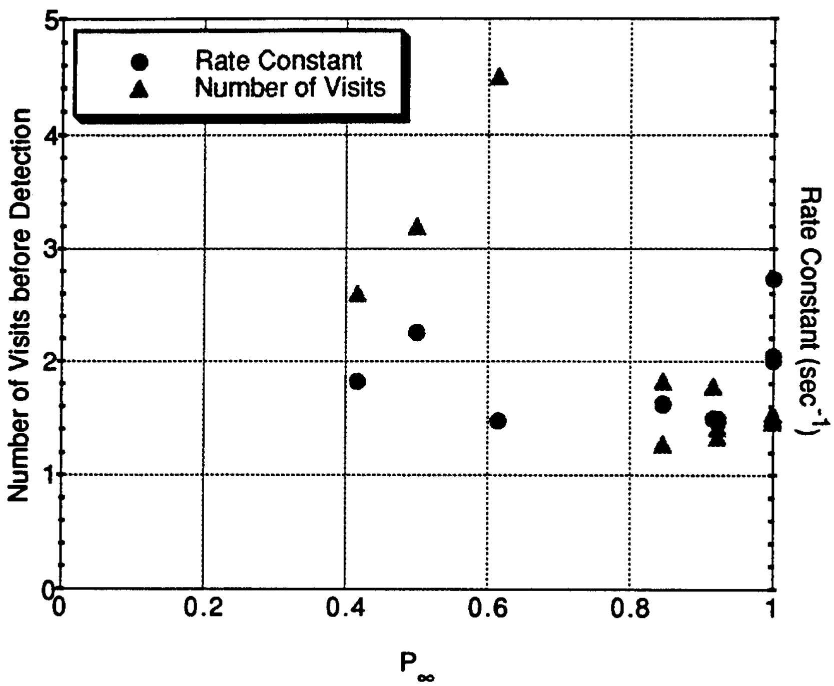

Figure II-3. Number of Visits Required for Detection and Rate Constants

III. SEARCH PHENOMENOLOGY

This section begins the detailed comparison of the predictions of the neoclassical model and the results of the data analysis. To make this comparison easier, the predictions of the neoclassical model will be given in each section in italics.

A. VISITS TO THE TARGET CANDIDATES

Prediction: Targets are not always detected on the first visit. The probability of detection on a visit is independent of time for a particular observer and target.

Figures III-1, III-2, and III-3 show the distribution of visits for the 101 data set, combining all targets and observers. As is shown in Fig. III-1, in 32 instances only 1 visit was made to the target, in 40 instances there were 2 visits, in 13 instances there were 3 visits, and so on. Since all of the observers in this restricted database detected the target in a given image, the 32 instances of a single visit were also one visit for detection. Figure III-2 shows that in 65 instances (out of 101) the target was detected on the first visit; in 22 instances 2 visits were required, in 6 instances 3 visits, and so on. This is consistent with a probability of detection on a single visit, P_{visit}, of 65 percent; the probability of detecting a target on the second visit is $P_{visit}(1-P_{visit}) \approx 23$ percent, and the probability of detecting a target on the third visit is $P_{visit}(1-P_{visit})^2 \approx 8$ percent. Note that these single visit probabilities are relatively high, indicating an easy-to-detect (when cued) target.

In terms of the neoclassical model parameters, the single visit search probability is given by:

$$P_{Visit} = \frac{\alpha_0}{W + J - J_0 + \alpha_0} \quad . \tag{III-1}$$

The mean time-on-target to detect a target, T_d, and the mean length of a visit to a target are given by:

$$T_d = \frac{1}{\alpha_0} \;\; ; \;\; T_{visit} = \frac{1}{W + J - J_0} \quad . \tag{III-2}$$

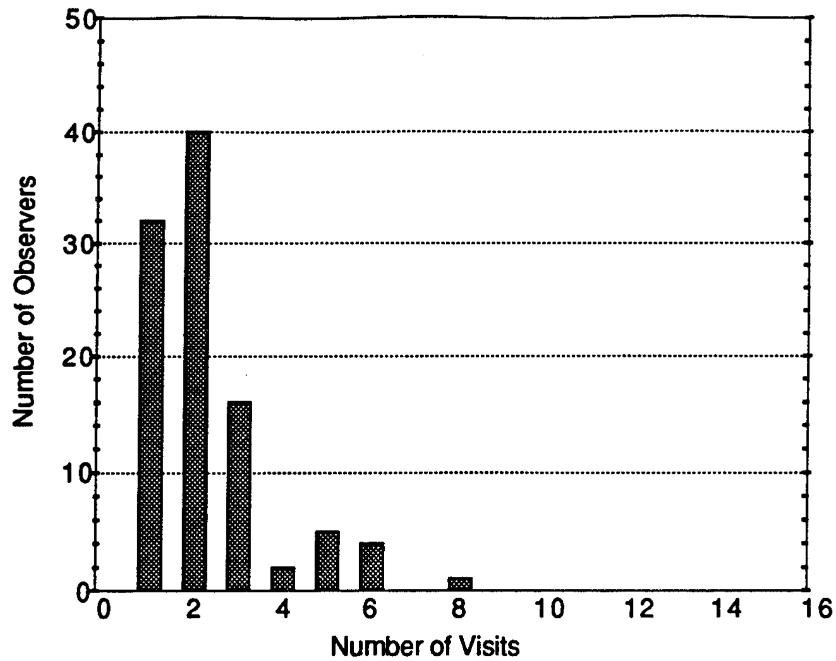

Figure III-1. Distribution of the Total Number of Visits to the Target 101 Subset

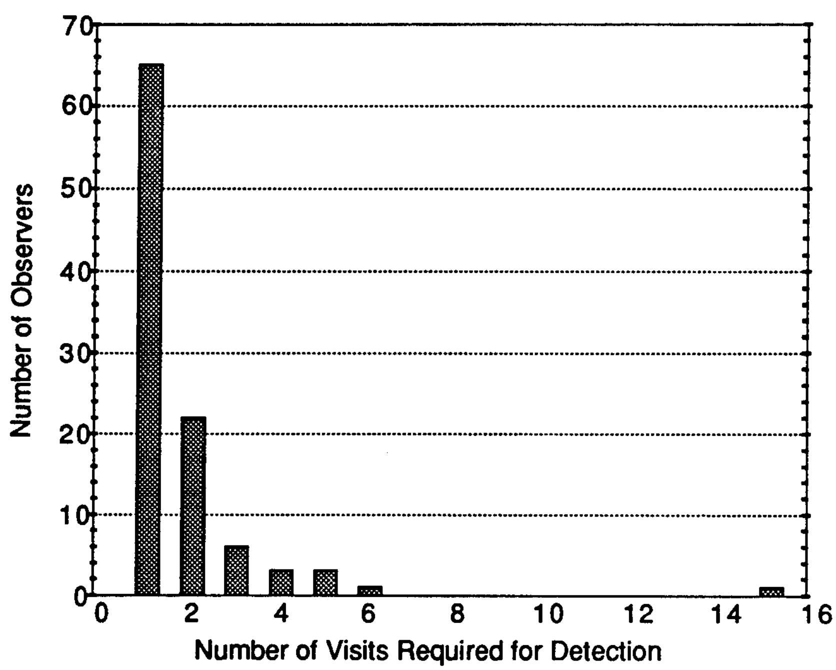

Figure III-2. Distribution of the Number of Visits Required for Detection in the 101 Subset

Thus the single visit probability can be written as:

$$P_{Visit} = \frac{T_{visit}}{T_d + T_{visit}} \quad . \tag{III-3}$$

The 65 percent probability of detection on a single visit would suggest that $T_{visit} \approx 2T_d$ for a typical target in the target set (since the targets are not all equivalent, the precise relationship will vary among the targets); however, the actual mean figures are closer to $T_{visit} \approx T_d$. This would lead to a single visit probability of detection of approximately 50 percent. The discrepancy implies that the distribution of either detection time or visit lengths is not exponential. As will be shown below, the detection visit itself (the visit during which detection is made) is non-exponentially distributed, being narrower, having no short visits. Such a narrower distribution will increase the single visit probability.

Prediction: A memory-less Markov process description of the search implies that the searcher will return to the target after detection.

This somewhat counter-intuitive result is, in part, borne out by the search data. Figure III-3 shows the distributions of visits after detection; 56 observers (of 101) never revisited the target, but 45 observers revisited the target at least once.

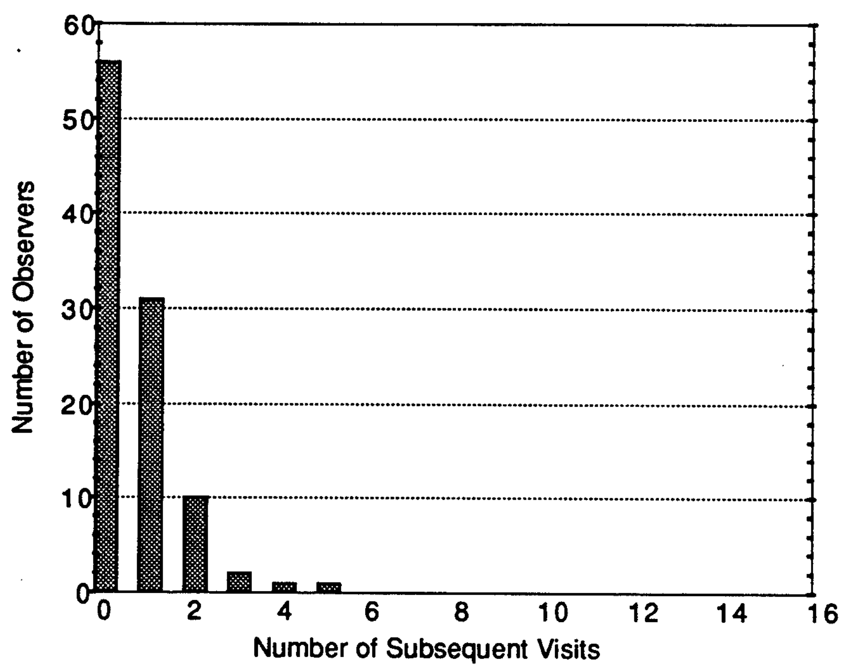

Figure III-3. Distribution of the Total Number of Visits Subsequent to Detection in the 101 Subset

B. VISIT LENGTHS

Prediction: In an ideal memory-less Markov process the pre-detection visits to the target, the detection visit itself (the visit during which detection occurs), and the post-detection visits would all be equivalent; the neoclassical model makes this assumption for simplicity. The length of the visits are exponentially distributed.

Figure III-4 shows the distribution of visit lengths for all observers and targets before detection.

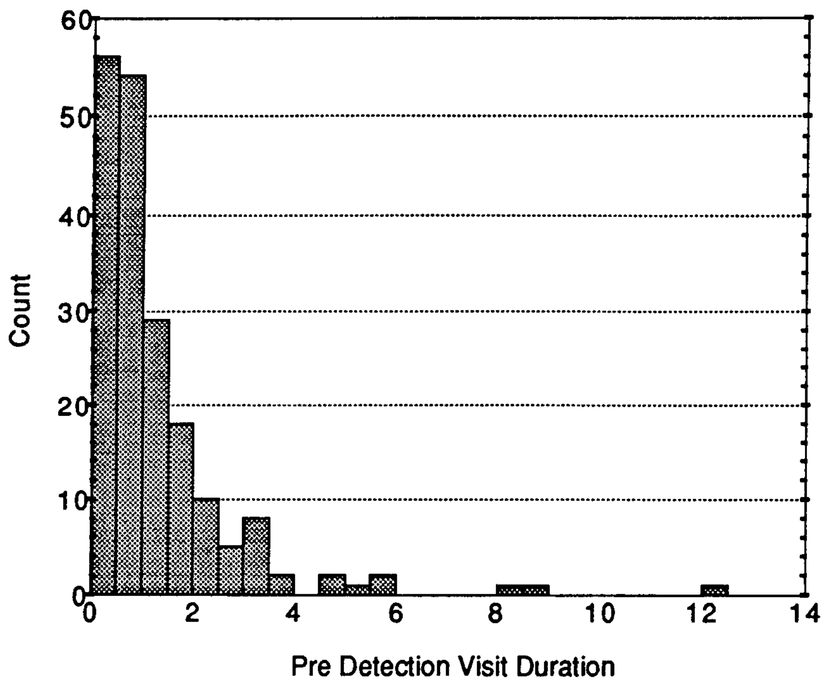

Figure III-4. Pre-Detection Visit Durations (Entire Database) (In Seconds)

The distribution of visit durations appears to be roughly exponential, consistent with the Markov description of the visits; the mean pre-detection visit is about 1.3 seconds. Any Markov process predicts an exponential distribution of visit durations. The cumulative distribution will be given below.

In Fig. III-5, the distribution of detection visit durations is given for the entire database. Note that the detection visits have a very different distribution with very few short visits and a much larger mean visit length of 2.4 seconds. One explanation for the stretching out of the detection visit would be to postulate that the observer is doing additional cognitive "processing" as a result of his decision to declare a detection. Note that

the distribution is compact with no long tail.[1] Thus, the duration of the detection visit itself is more like a normal than an exponential distribution.

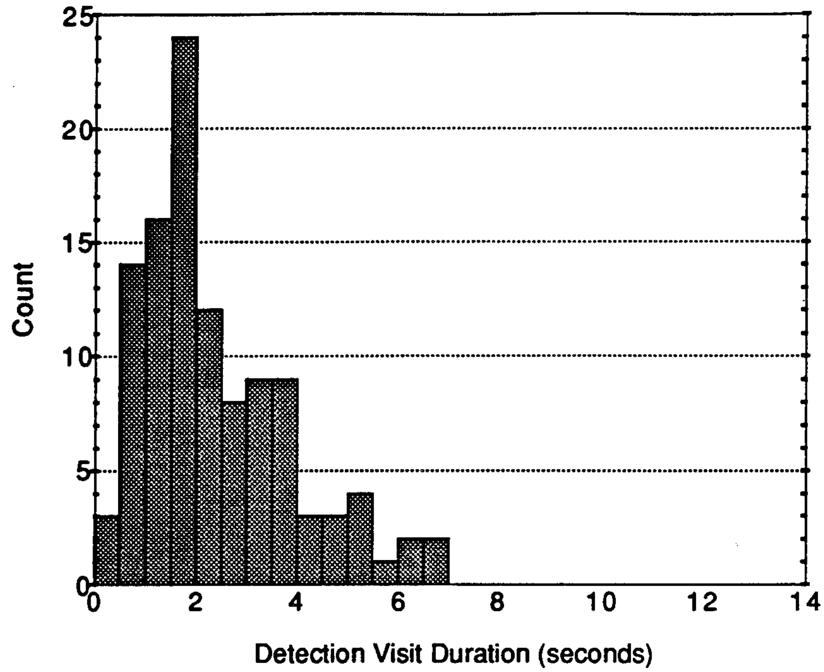

Figure III-5. Detection Visit Durations (Entire Database)

Finally, Fig. III-6 shows the distribution of the duration of visits that are subsequent to detection for the entire data set. The mean visit length is somewhat shorter than in the pre-detection case (≈1.2 seconds) but again resembles an exponential distribution.

1 The particulars of the experiment required the observers to perform certain tasks whenever a target was declared. To the extent possible, the times were corrected for this activity.

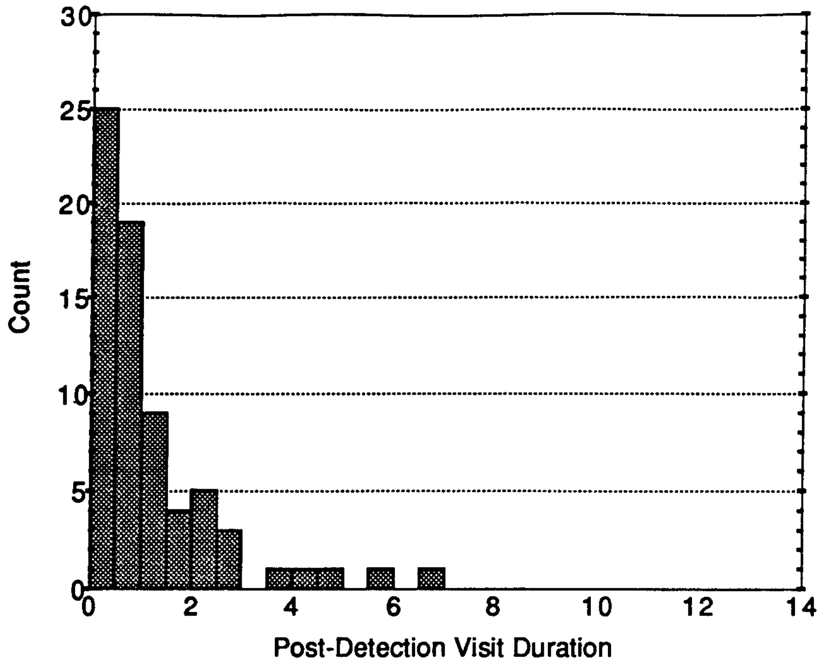

Figure III-6. Visit Durations for Post-Detection Visits (Entire Database)

Figure III-7 shows a scatter plot of all the visit durations under 6 seconds by observer. The variations between observers are interesting if not conclusive.

- Observer number 2 is the only observer with long post-detection visits.
- Observers 2 and 8 are the only observers with consistently pre- and/or post-detection visits that are significantly longer than the detection visit.
- Observer 12 detects many targets in longer than average detection visits that are typically first and only visits to the target.
- Note the large scatter in the detection visit durations; the tighter distribution of pre-detection visit times, and shorter post-detection visits.

Figure III-8 shows the durations averaged over observer for each of the 11 targets (entire database). For 9 of the 11 targets there is good agreement between the pre- and post-detection mean visit durations.

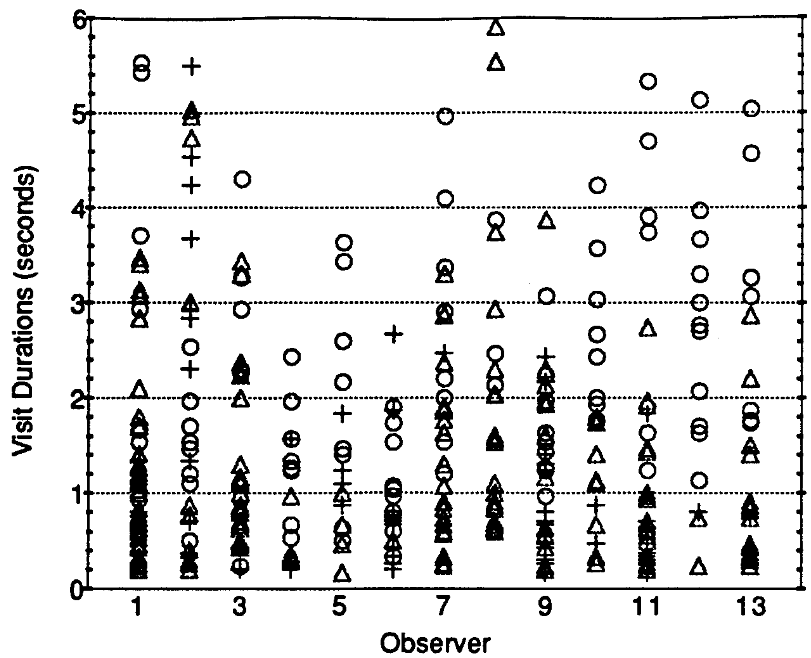

Figure III-7. Scatter Diagram of Pre-Detection (triangles), Post-Detection (crosses), and Detection (circles) Visit Durations Under 6 seconds (Entire Database)

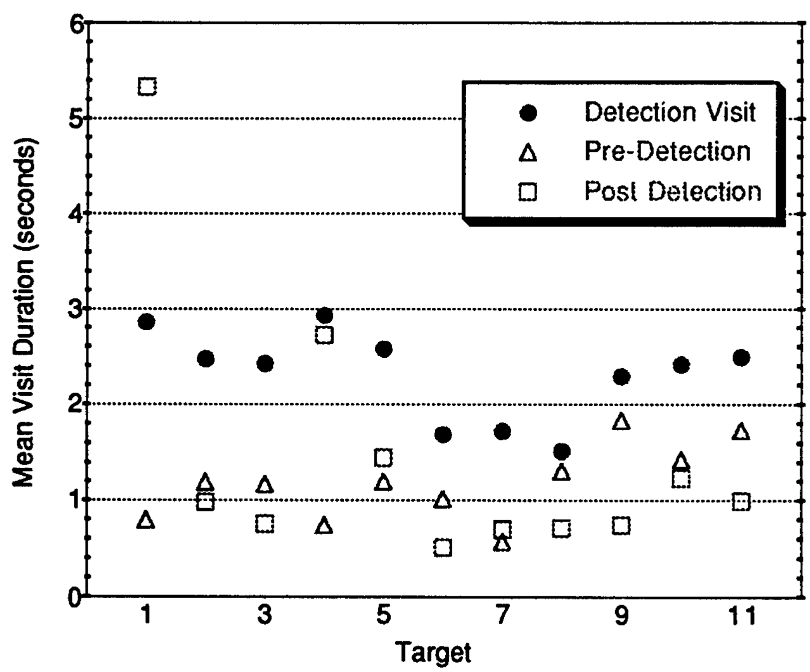

Figure III-8. Average Visit Durations by Target (Entire Database)

Figure III-9 shows that the variations among targets are relatively small for the pre-detection visit duration. It therefore is reasonable to combine targets to look at the details of the distribution of visit durations. Figure III-9a shows the cumulative distribution of visits for all targets and observers from the complete database of all observers that ever visited the target at least twice. The data are extremely well represented by a single exponential (shifted to account for the data smoothing which requires visits to be at least 0.167 seconds) over the whole range with a time constant of approximately 0.92 seconds or an eigenvalue $\lambda = (W + J - J_0) = 1.1 \text{ sec}^{-1}$. Figure III-9b shows the detail of the fit for short times. It is remarkable that the fit is so good, given that the 11 targets were combined and 13 different observers included.

Figure III-10 gives the individual estimates by target of the time constant with the 1-standard deviation error bar indicated. Merging the targets is certainly acceptable at the 1.5 standard deviation level.

Figure III-11a shows the post-detection visit cumulative distribution (Fig. III-11b shows the detail at short times). The fit to a single exponential is again reasonable with a slightly larger eigenvalue (1.25 seconds^{-1}) corresponding to a shorter time constant of 0.8 seconds.

The overall conclusions from the examination of the visit lengths are:

1. The assumption of a Markov search process before target detection is consistent with the data for pre-detection and post-detection visits.
2. The duration of the detection visit is longer than the typical pre-detection visit; the most obvious explanation being extra cognitive processing upon making the decision.
3. The distribution of post-detection visits appears to differ from the pre-detection visits significantly. This implies some learning in the search process so that a memory-less Markov search process is a simplifying approximation to a more complex behavior. This learning is of importance for multiple-target searches but does not affect the single target problem.

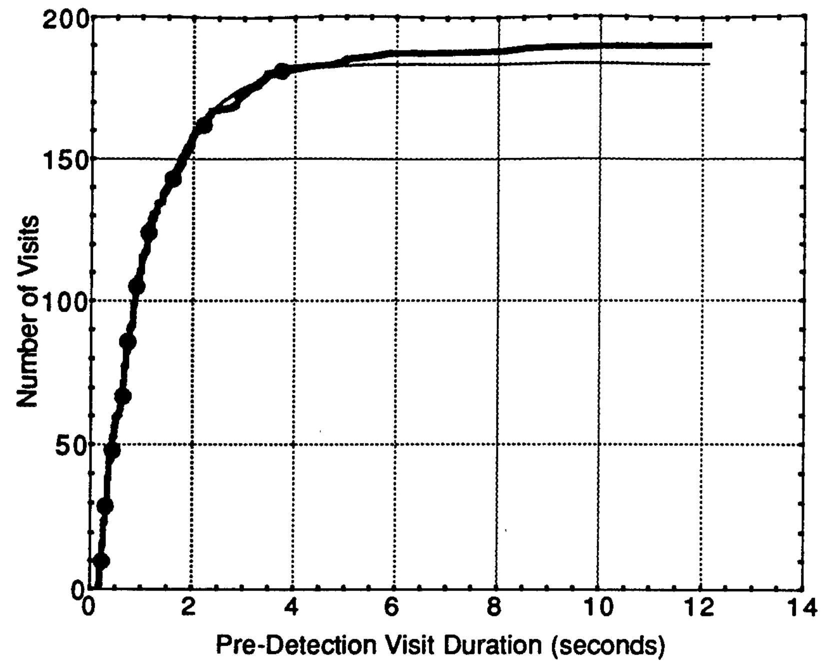

Figure III-9a. Cumulative Pre-Detection Visit Durations (Entire Database)

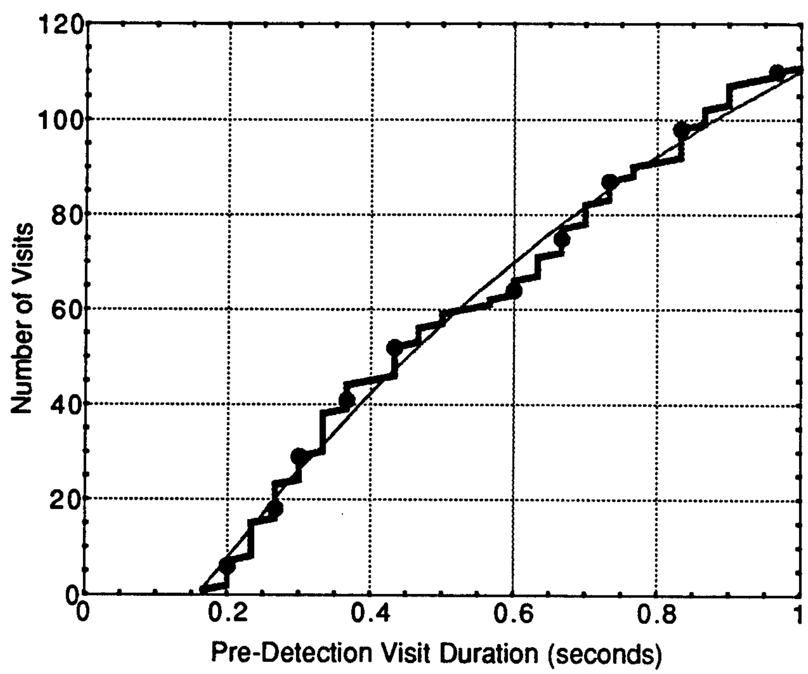

Figure III-9b. Cumulative Pre-Detection Visit Durations (Short Times)

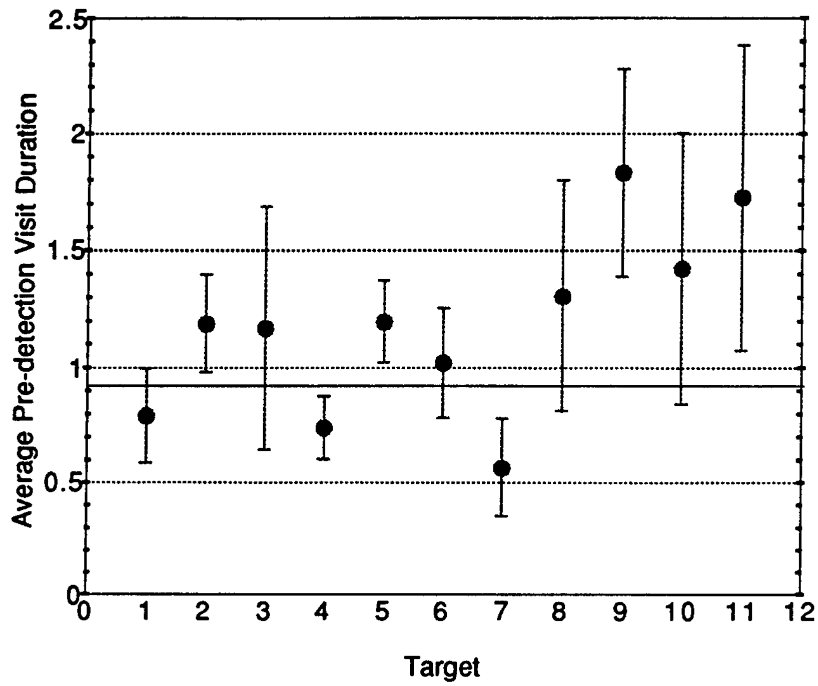

Figure III-10. Average Pre-Detection Visit Durations by Target (Entire Database)

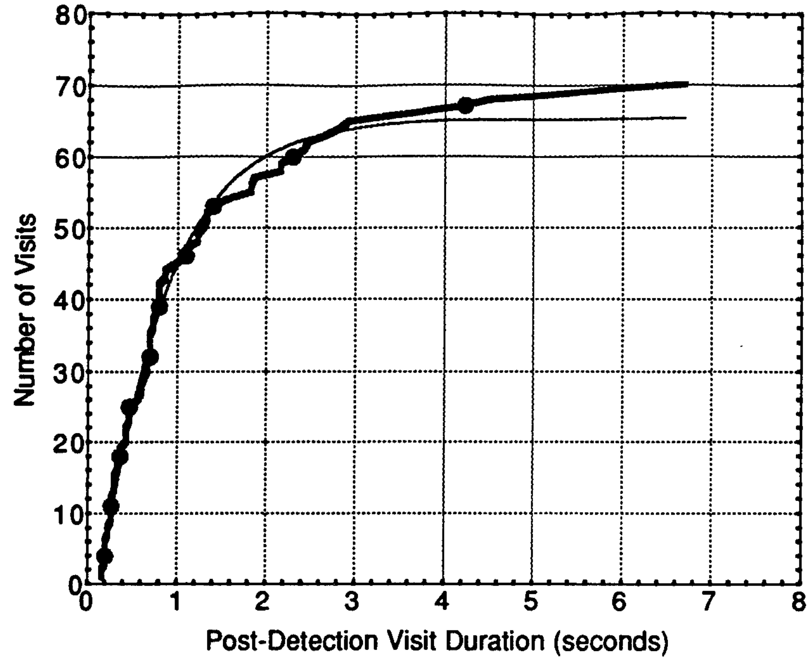

Figure III-11a. Cumulative Post-Detection Visit Durations (Entire Database)

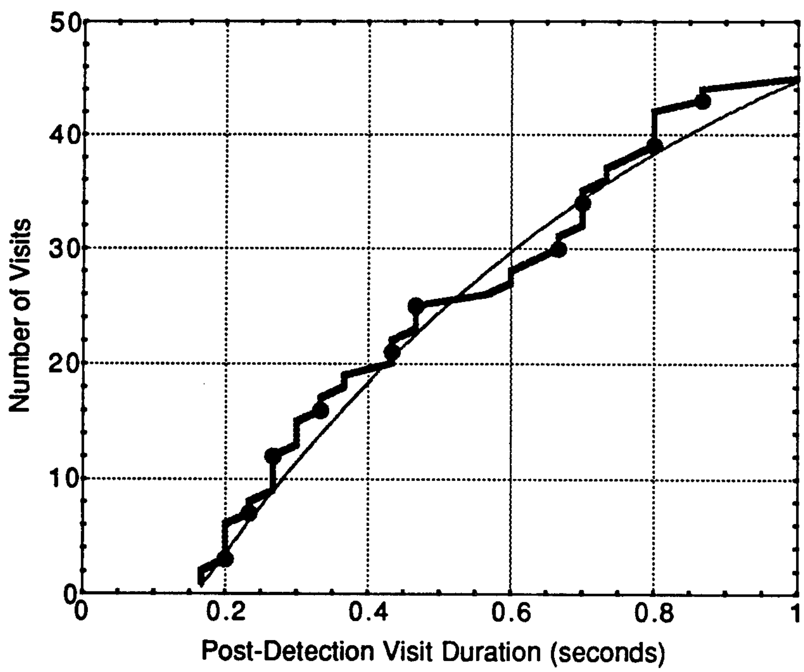

Figure III-11b. Cumulative Post-Detection Visit Durations (Detail)

C. VISIT SEPARATIONS

The gaps or separations between visits in any Markov process are a probe of the search process. For simplicity in this preliminary analysis, the different targets and observers will be pooled; as in the visit durations, the estimates of the separations are roughly consistent with such pooling.

1. First Visit

Prediction: The distribution of the time to the first visit is described by one ($J = S$) or two exponentials.

The most important single time in this experiment is the time until the first visit to the target since 65 percent of the observers detect on the first visit. The cumulative distribution of these times for all observers and targets is shown in Fig. III-12a for all targets pooled together and the subset removing the (harder to detect) targets 1, 4, and 5. There were 15 instances for which the observer was cued to the target at t = 0 (in most of these cases the target was located at or near the center of the image, which is a natural place for the observer's initial eye location). Therefore, the figure shows an immediate jump to 15 observers. Then, there is a delay before a rapid rise that asymptotes at about 3 seconds, followed by a slow increase out to nearly 15 seconds that is primarily due to targets 1, 4, and 5. The behavior up to 3 seconds is illustrated in Fig. III-12b. The initial delay is too long to be a consequence of data smoothing and must be taken to be a real effect.

Neither effect is consistent with the simplest Markov model; for example, a model with only two states—examining and not-examining the target (equivalent to $J = S$). Such a model always gives rise to an exponential distribution with a single exponent and no delay and no long tail. Figure III-12 shows a competition between at least two processes and possibly three (one process for the initial delay, one for the rapid rise, and one for the long tail). There are several possible choices for the competing processes.

First, the observers may be subject to an orientation delay. This can be modeled by convolving the delay distribution with the model predictions without delay. For example, for a single exponential model in the case of no delay ($J = S$), adding a delay leads to a two-exponent prediction for the first visit time. [See Nicoll (1994).] For $J \neq S$, such a delay leads to a three-exponent prediction and a possibly cubic time dependence near t = 0.

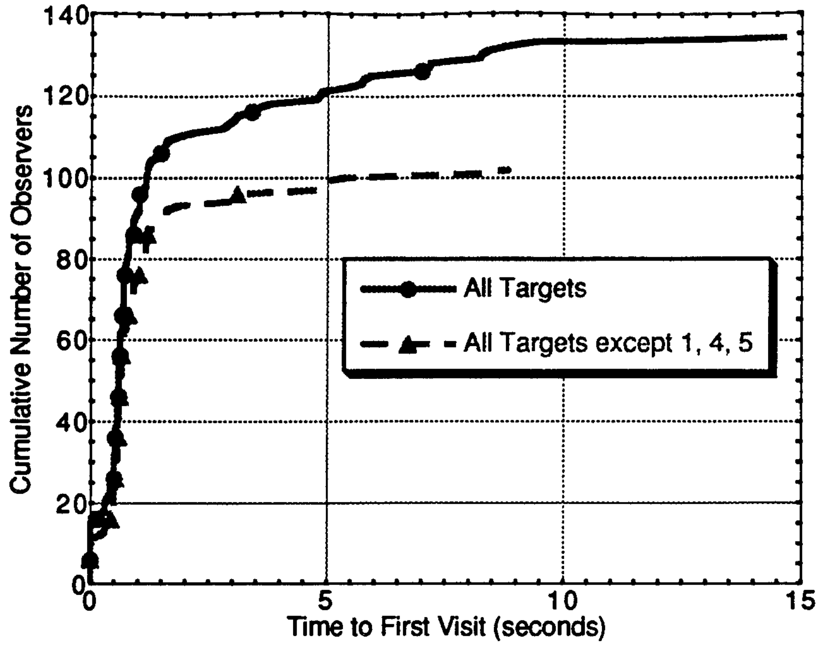

Figure III-12a. Cumulative Distribution of Times to First Visit

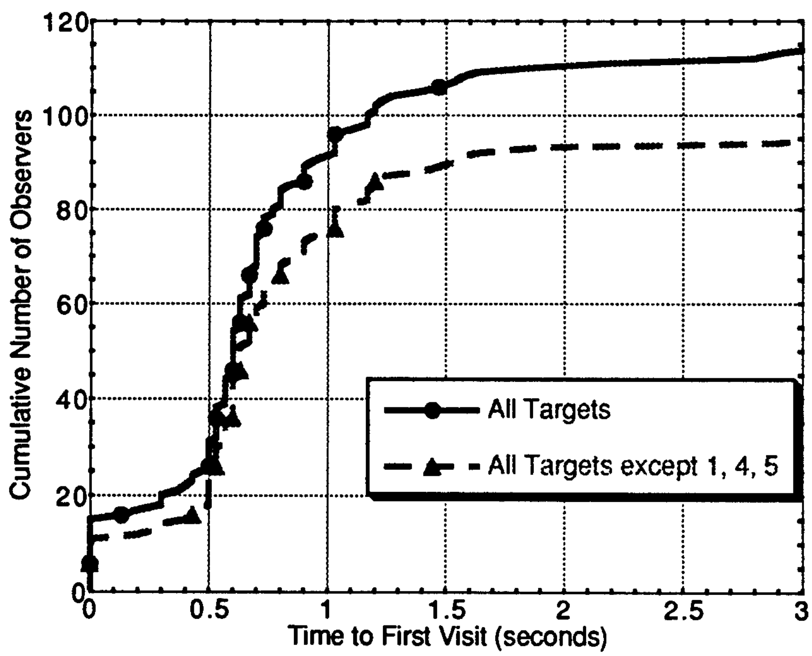

Figure III-12b. Cumulative Distribution of Times to First Visit (Detail)

Second, the neoclassical model predicts, in general, a two-exponent form for the time of first arrival. An apparent delay would be consistent with the form of the neoclassical prediction if the observers typically began the search process at a point of interest. Thus, the observer would either start on the target (as in 10 instances) or would begin on a non-target point of interest or distracter and could only move on to the target after an examination of the distracter. A delay of the order of 1 second would be the expected consequence.

Third, the long tail may result from a complex distraction process in which the observer spends an excessive amount of time on a distracter. As noted above, the detection visit for the target was abnormally long. The long tail may be due to the observer spending a correspondingly large amount of time on other points of interest. Further data analysis will be required to address this possibility. The long tail was primarily generated for the targets with lower P_∞. The lower value may reflect an abandonment of the search in situations in which the observer has spent an excessive amount of time on the distracters.

For observers who do not start at the target, the mean time until the first visit in the neoclassical model is given by:

$$<t_1>=\frac{1}{p_{eq}(W+J)}[1+w(0)\frac{J_0-S_0}{(W+S)}] \quad . \qquad \text{(III-5a)}$$

Here, p_{eq} is the equilibrium fraction of the time the observer spends on the target:

$$p_{eq}=\frac{(S_0W+J_0S)}{(W+J)(W+S)}=\frac{T_{visit}}{T_{visit}+T_{gap}} \quad , \qquad \text{(III-5b)}$$

where T_{visit} is the mean length of a visit and T_{gap} is the mean separation between visits subsequent to the first visit.

$$T_{visit}=\frac{1}{W+J-J_0} \quad . \qquad \text{(III-5c)}$$

The arrival time distribution for the first or subsequent visits is:

$$P_{arrive}(t)=e_1e^{-\lambda_1 t}+e_3e^{-\lambda_3 t} \qquad \text{(III-6a)}$$

$$\lambda_{1,3}=\frac{R+J_0\pm\sqrt{(R+J_0)^2-4[S_0W+J_0S]}}{2} \qquad \text{(III-6b)}$$

$$e_i=\frac{\lambda_j-J_0p(0)-S_0w(0)}{\lambda_j-\lambda_i} \quad , \qquad \text{(III-6c)}$$

where p(0) = 1 – w(0) is the initial probability of the observer examining a distracter. The initial rate of arrival is $w(0)S_0 + p(0)J_0$; thus, a small initial rate would be consistent with $p(0) \approx 1$, $J_0 << S_0$ at least qualitatively. If this were the case, one might expect to be able to detect the need for two exponents in the gap separation.

2. Pre-Detection Visit Separations

Prediction: The distribution of the gaps between visits is described by one ($J = S$) or two exponentials.

Figure III-13 shows the mean gap time average over observer by target. Gaps of longer than 6 seconds were removed from the average as these long tails (see Fig. III-14, below) distort the averages significantly. The error bars give the statistical error bars in the means given the number of visits, assuming an exponential distribution. There is a reasonable overlap, providing justification for the pooling of targets.

Combining the average visit time and average gap, an estimate of the equilibrium probability of examination of the target can be given. These are shown in Fig. III-14, with the error bars implied by the errors in the visit and gap times. Again, within the statistical error, there is justification for pooling the targets. The values of p_{eq} are very large—of the order of 50 percent: the observers spent half their time examining the target. This is an indication that the targets in this data set were relatively conspicuous and that the other points of interest did not act as significant distracters.

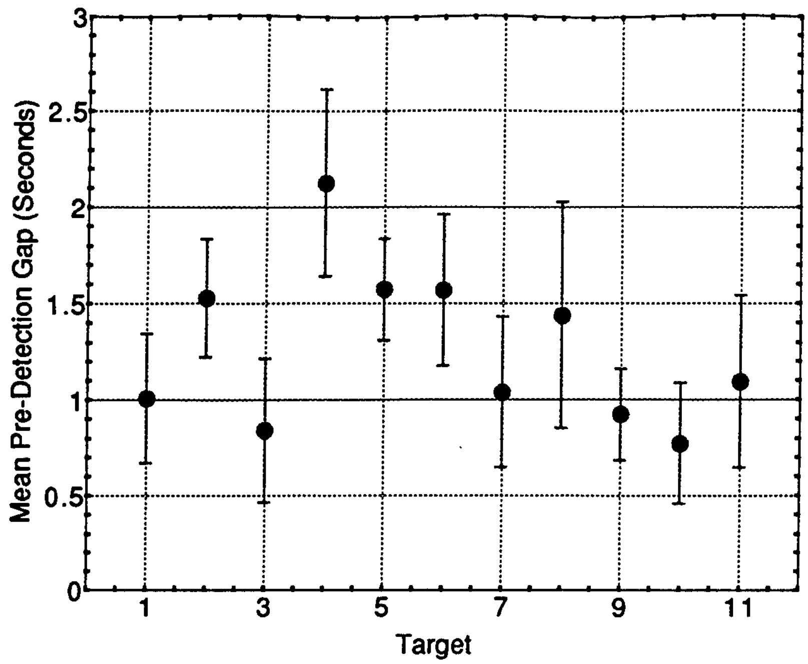

Figure III-13. Mean Pre-Detection Gap Times by Target

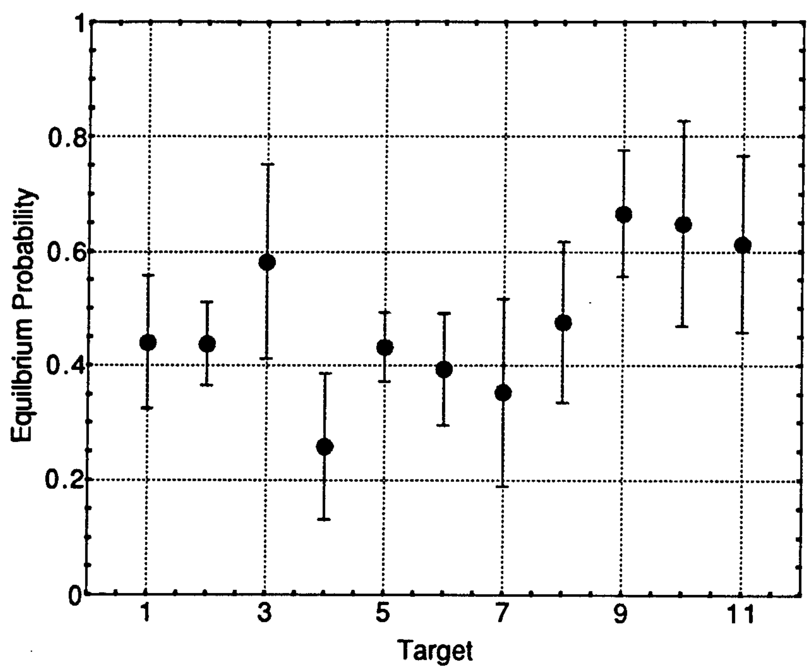

Figure III-14. Estimated Equilibrium Probability of Examination by Target

Figure III-15a shows the distribution of visit separations before detection (Fig. III-15b shows the detail for gaps of up to 3 seconds) along with a single exponential fit [with eigenvalue $\lambda \approx 0.87$ sec^{-1} (corresponding to a time constant of 1.14 seconds)]. Just as for the first visit time distribution, there is a long tail after 6 seconds. The data smoothing forces the minimum length of the gap to be 0.23 seconds. The visit to a single exponential is not as good as for the visit length, even if the long tail is ignored. Figures III-15c and III-15d show the data restricted to 6 seconds and refit with a single exponential with exponent $\lambda \approx 0.98$ sec^{-1} (corresponding to a time constant of 1.02 seconds). There are small but persistent deviations. It is hard to conclude that this demonstrates that more than one exponent is required to fit the data. However, the deviation is small but in the correct direction for $J \neq S$ (see Appendix A), but the data are insufficient to establish the precise values of the parameters accurately.

If one assumes that the difference, $S_0 - J_0$, is small, then Eqs. III-5 and III-6 simplify:

$$\lambda_1 = R - \frac{W\,(S_0 - J_0)}{R - J_0} \tag{III-7a}$$

$$\lambda_3 = J_0 + \frac{W\,(S_0 - J_0)}{R - J_0} \tag{III-7b}$$

$$\begin{aligned} e_1 &= \frac{W(S_0 - J_0)(S - J)}{(W + S - J_0)^2 (W + J - J_0)} \\ e_3 &= 1 - e_1 \end{aligned} \tag{III-7c}$$

If one assumes that all the values of J_i are proportional to the corresponding S_i, $J_i = \kappa\, S_i$, then the amplitude reduces to

$$e_1 = \frac{p_{eq}}{(1 - p_{eq})^3} \frac{WS}{(W + S)} (1 - \kappa)^2 \quad . \tag{III-7d}$$

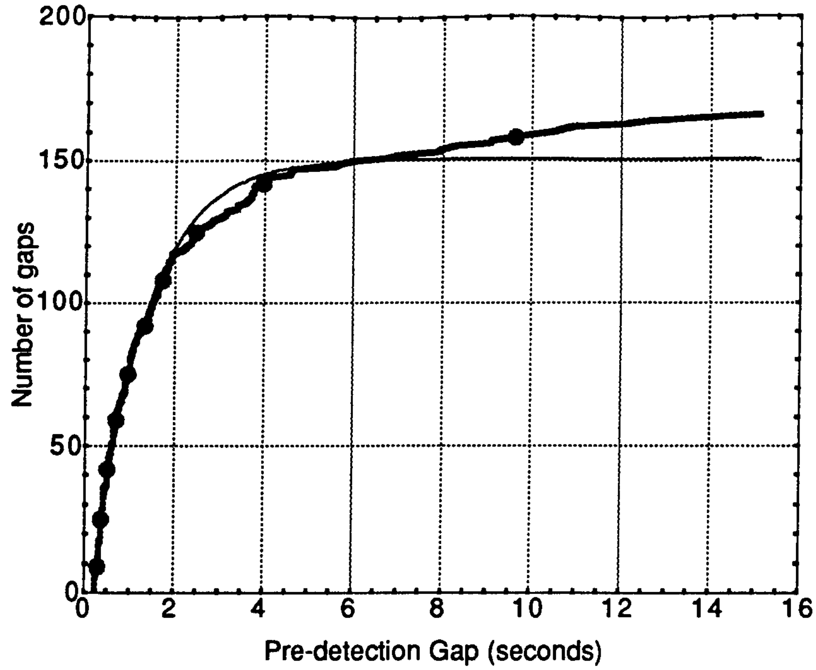

Figure III-15a. Cumulative Pre-Detection Visit Separations

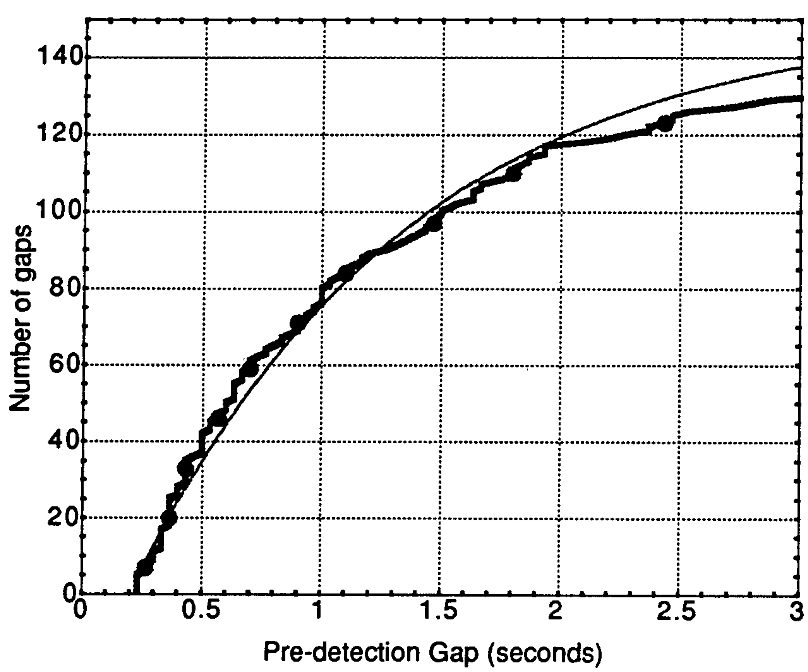

Figure III-15b. Cumulative Pre-Detection Visit Separations (Detail)

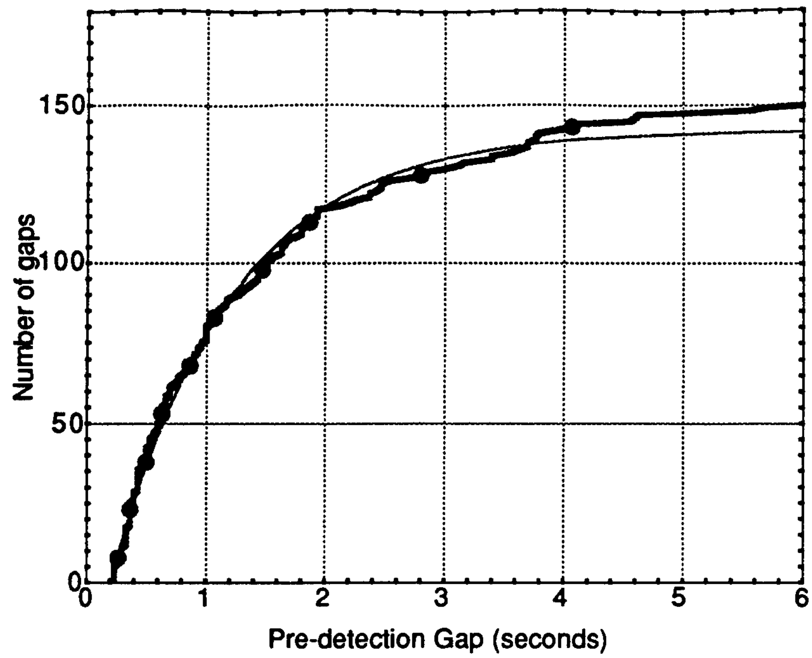

Figure III-15c. Cumulative Pre-Detection Visit Separations (Data for fit restricted to be less than 6 seconds)

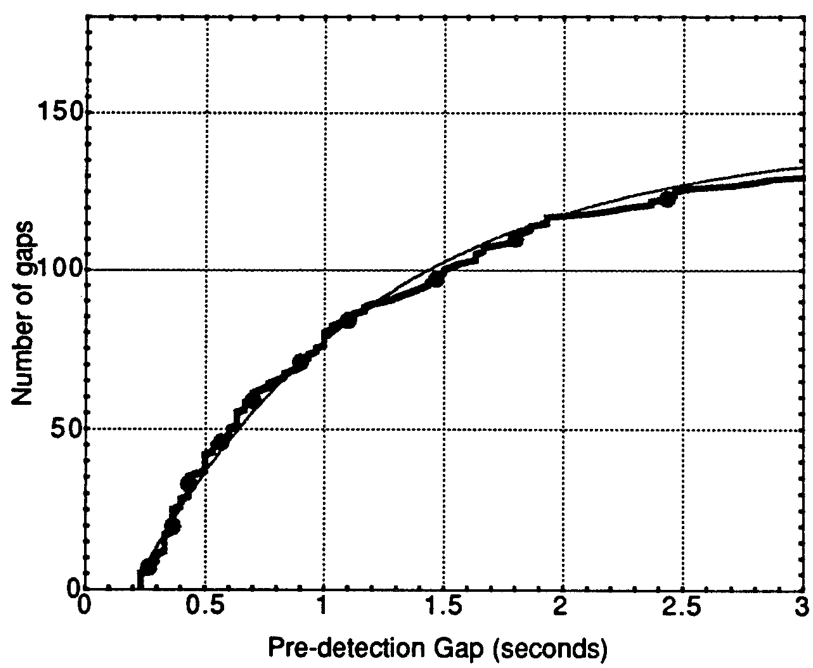

Figure III-15d. Cumulative Pre-Detection Visit Separations (Data for fit restricted to be less than 6 seconds, Detail)

Since p_{eq} is ≈ 0.5 and $W \approx S$, this amplitude is approximately $(1 - \kappa)^2$. Thus, if κ is close to one, this amplitude is very small and hard to measure. Using the full neoclassical two-exponential fit does improve the fit; however, this is not surprising since using the two-exponent form increases the number of fitting parameters. The ratio of the exponents is approximately $\lambda_1/\lambda_3 = 1/p_{eq} \approx 2$, so one is only fitting the amplitude of the faster exponent. Although the fits are not compelling they give a value of κ between 0.2 and 1.0. However, since there are a number of other explanations of the small deviations from a single exponent, the conclusion is that the pre-detection visit separations are consistent with the simpler $J = S$ case but the case of $J \neq S$ cannot be excluded. Similar results are obtained if the low P_∞ targets (1, 4, 5) are removed from the pool, as shown in Figs. III-16a and III-16b. There is a small indication that the slope changes in the vicinity of 1 second, indicating the possibility of 2 exponents.

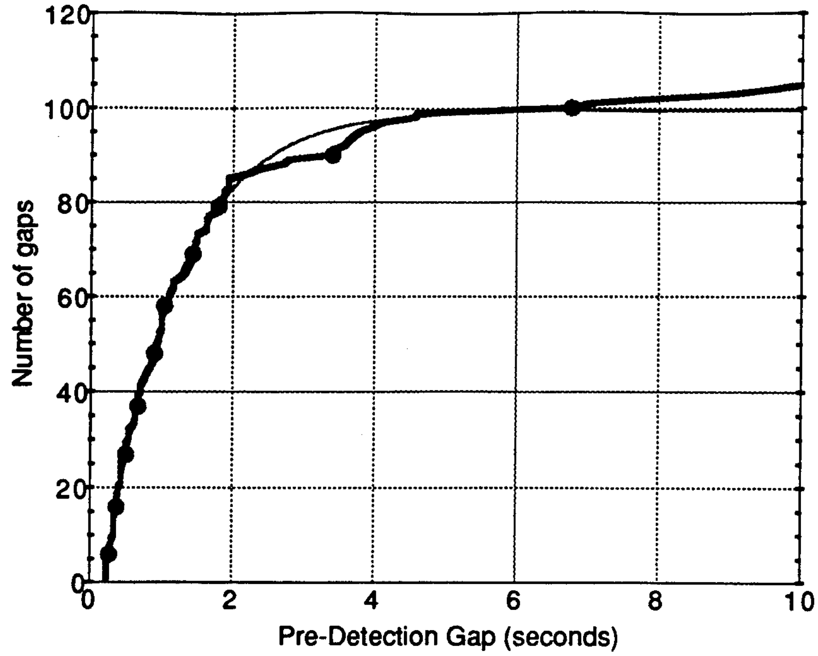

Figure III-16a. Cumulative Distribution Pre-Detection Gap— Omitting Targets 1, 4, and 5

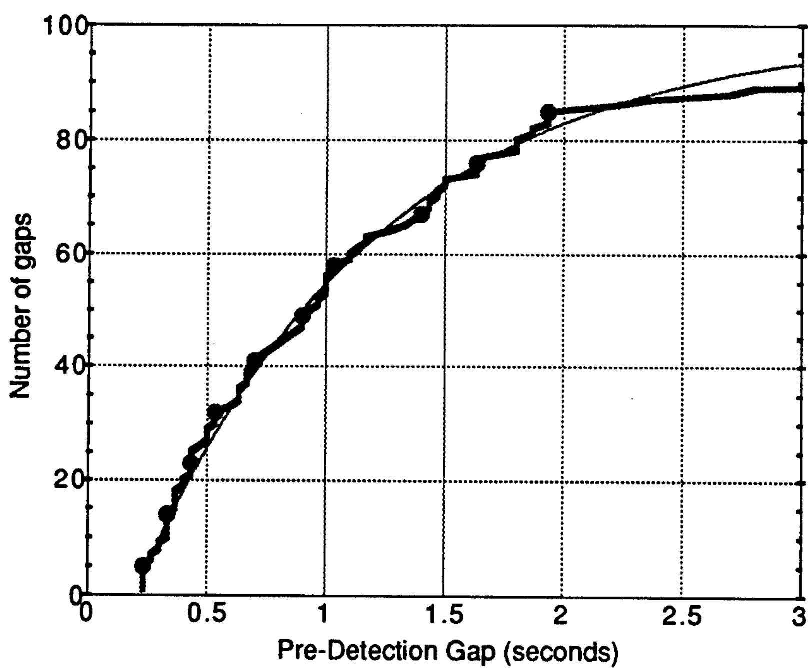

Figure III-16b. Cumulative Distribution Pre-Detection Gap— Omitting Targets 1, 4, and 5 (Detail)

3. Post-Detection Visit Separations

Prediction: For a memory-less Markov process the gaps after detection will be distributed in the same way as gaps before detection.

For completeness, we include the post-detection gap distributions in Figs. III-17a, III-17b, and III-17c. Figure III-17a shows the fit with an exponential with $\lambda \approx 0.73$ sec^{-1} corresponding to somewhat longer gaps (1.5 seconds) than in the pre-detection case. Again there is a long tail indicating a deviation from exponential behavior at very long times. Figure III-17b shows the short time detail. There is an excess number of very short gaps between visits. Fitting just the region out to 5 seconds gives an exponent of 1.5 sec^{-1} and just as bad a fit (see Fig. III-17c). The difference between the post-detection and pre-detection distributions indicates considerable learning in the search process.

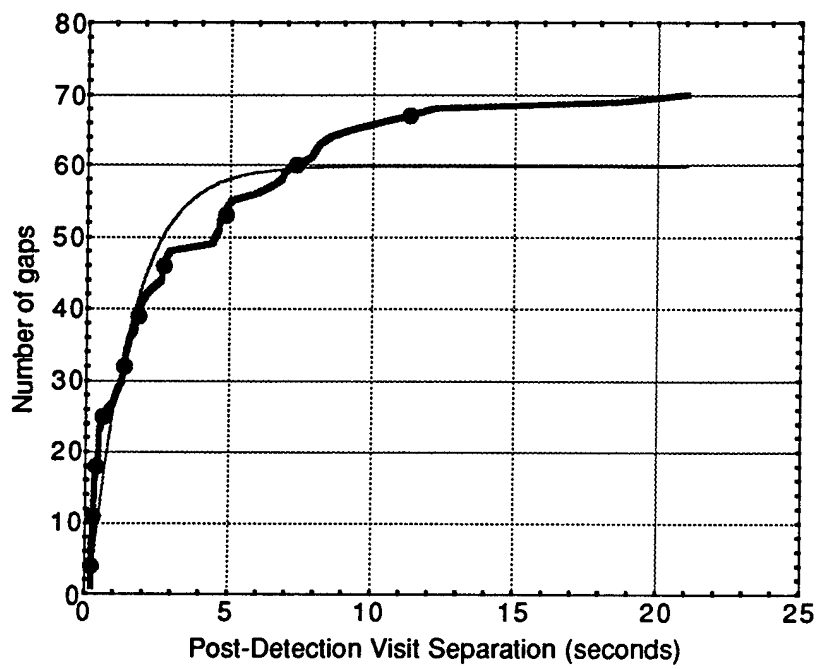

Figure III-17a. Cumulative Distribution of Post-Detection Visit Separations

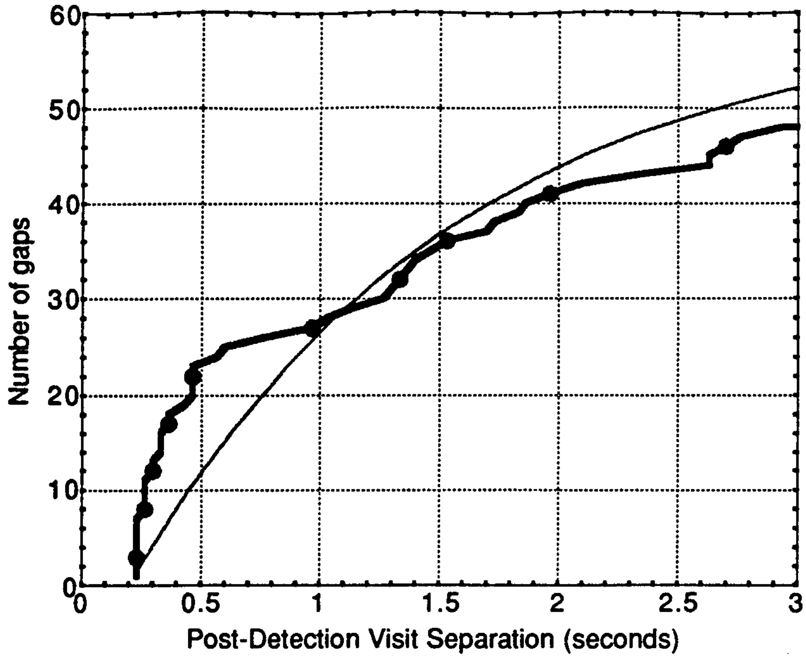

Figure III-17b. Cumulative Distribution of Post-Detection Visit Separations (Detail)

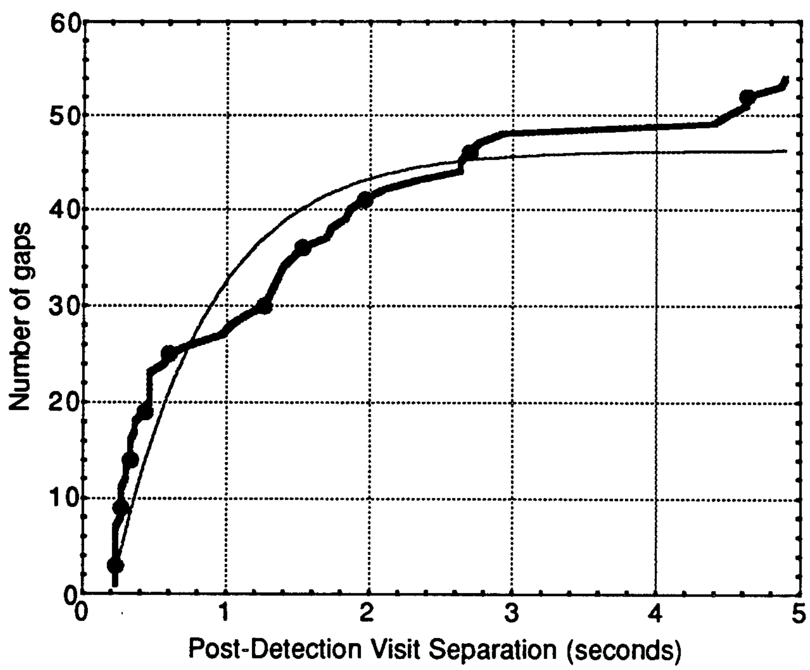

Figure III-17c. Cumulative Distribution of Post-Detection Visit Separations (< 5 seconds)

4. Summary

The distributions of the first visit times and the visit separation times, both pre-detection and post-detection, show that different processes are involved. This makes it all the more surprising that the mean time to first visit, $<t_1>$, and the mean pre-detection separation between visits, $<T_s>$, are close (compare to Fig. III-18). The large discrepancies are in the direction of larger times to first visits, which could be accounted for by capture of the observer by a distracter.

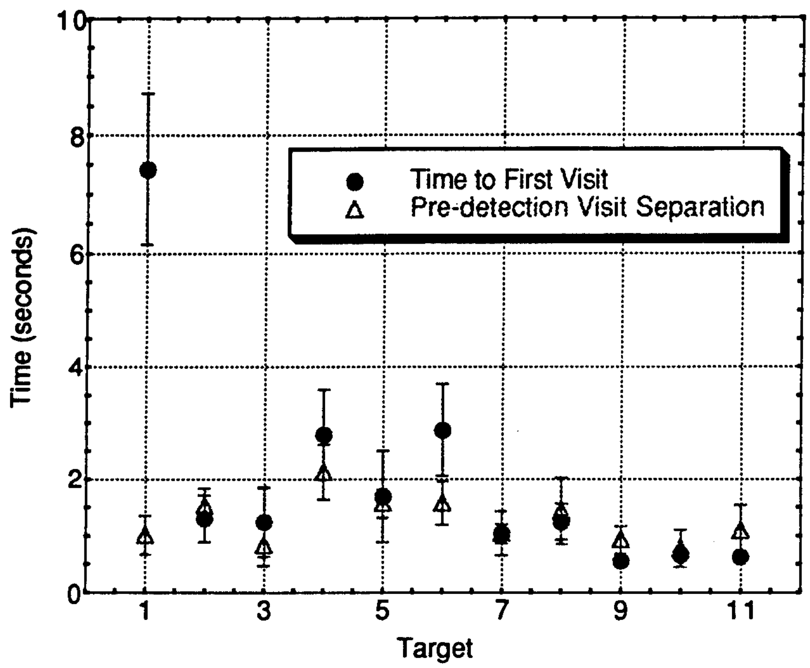

Figure III-18. Pre-Detection and Post-Detection Visit Separation and Time to First Visit Averaged over Observer by Target

From an analysis perspective, the search is more complicated than even the full neoclassical model if examined in detail. The first visit exhibits a long delay followed by a rapid search. Subsequent gaps indicate a more leisurely search. The distributions of the first visit times and subsequent pre-detection visit separations show an extremely long tail indicating some probability of extensive delays in the search particularly for the lower P_∞ targets. The shape of the pre-detection gap distribution is consistent with the simpler version of the neoclassical model with $J = S$; the post-detection distribution is not. There is therefore considerable evidence that the neoclassical model would need further extensions to describe the distribution of first visits.

However, as noted above, the <u>mean</u> time to the first visit agrees with the <u>mean</u> pre-detection visit separation, as predicted by $J = S$. If this conclusion holds true for other targets and backgrounds, then for many purposes the differences in the detailed distributions could be ignored and the neoclassical model could be used without change.

If we accept the results for the pre-detection separation and assume the $J = S$ limit with a time constant $\lambda \approx 0.9$ sec^{-1}, we can try to reconcile the separation time distribution and the first visit distribution by assuming an initial orientation delay followed by a normal or near normal separation. This would require a delay with a time constant of roughly 0.5 second and this would disrupt the agreement with the average time. If one considers a general two-step visit process [see Nicoll (1994)] with an exponentially distributed delay process with exponent η transitioning to a search process with effective exponent λ, then the cumulative distribution of first arrival times would be:

$$P_{\text{arrival}}(t) = 1 - \left(\frac{\eta}{\eta - \lambda} e^{-\lambda t} - \frac{\lambda}{\eta - \lambda} e^{-\eta t}\right) \quad . \tag{III-8a}$$

The average arrival time for this distribution would be:

$$< t_1 > = \frac{1}{\eta} + \frac{1}{\lambda} \quad . \tag{III-8b}$$

Fitting an expression of this form to the first arrival time data leads to the result shown in Fig. III-19 with degenerate exponents ($\eta \approx \lambda \approx 0.46$ sec^{-1}) showing no agreement with the visit separation effective exponent. Beyond the disagreement with the visit separation time constant, it is not a particularly good fit! The fact that the fit forces the exponent to degenerate is another sign that a fit of this form is inappropriate.

The clear conclusion is that the first visit is more complex than the subsequent visits. This will require further modeling and data analysis to clarify the results. It is not clear whether the agreement between the mean time to first visit and the mean visit separation is only a coincidence.

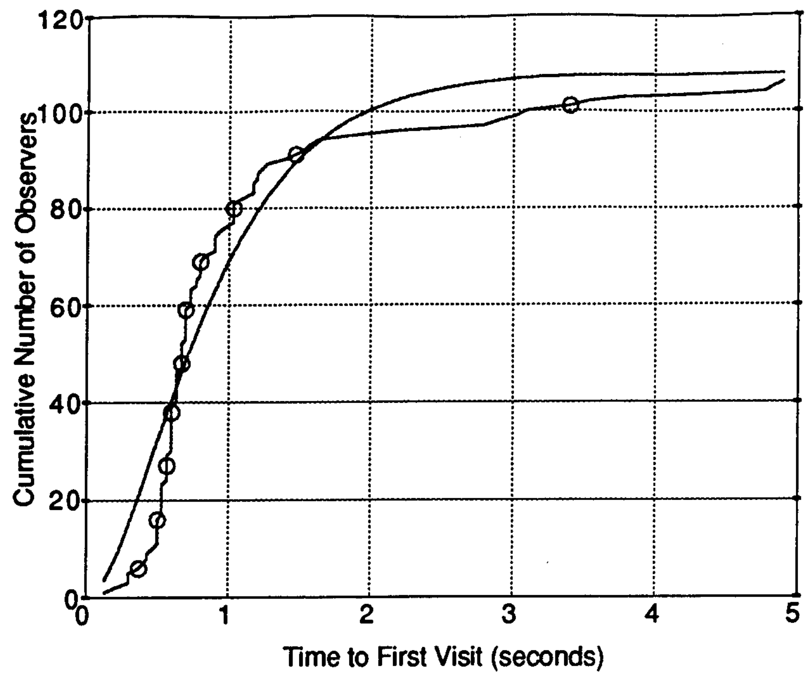

Figure III-19. Cumulative First Arrival Time Distribution With Two-Process Fit

D. CONCLUSIONS

The conclusions reached must necessarily be tentative. The targets in these images were sufficiently conspicuous that the observers spent approximately 50 percent of their time examining the targets. This may lead to conclusions not representative of less conspicuous targets. However, some general conclusions can be made:

1. Not all observers detect on the first visit. The number detecting on the second and subsequent visits is consistent with a constant probability of detection per visit.

2. Observers do re-visit targets after detection. The typical visit is shorter than pre-detection visits but there are exceptions.

3. Gaps between visits (pre-detection) are exponentially distributed. The results are consistent with the simplified limiting case of the neoclassical model with $J = S$.

4. The mean time to the first arrival agrees relatively well with the mean time between visits consistent with the simplified limiting case of the neoclassical model with $J = S$.

5. The details of the first visit are more complex than assumed in the neoclassical model.

IV. DETECTION PHENOMENOLOGY

Prediction: The probability of detection is exponential in the time on target, T.

One of the underlying assumptions of the neoclassical model is that the probability of detection is exponential in the time on target, T.

$$P_d(t) = 1 - e^{-\alpha T} \quad . \tag{IV-1}$$

To test this assumption, we could pool all the targets, effectively assuming that a single value of α suffices to describe all the test targets. Since a single exponential is anticipated, we can normalize the detection time data for each of the targets by dividing the time-on-target to detect, T_d, by its average for each target, $<T_d>$. Then the total number of detections should be given by

$$N_d(t) = \text{Const}(1 - e^{-T_d/<T_d>}) \quad . \tag{IV-2}$$

Using this method the data can be pooled, even if the values of α differ markedly. The result is shown in Figs. IV-1a and IV-1b along with a fit of the form implied in Eq. (IV-2). Near the origin, we have again taken into account the censoring of the data induced by the smoothing technique; visits to the target cannot be shorter than 0.167 seconds and thus it is difficult to produce a value of T_d shorter than 0.167 seconds. The fit is remarkably good and provides firm support for the assumption of an exponential detection model.

Prediction: The number of targets detected is described by two (J = S) or three exponentials.

Figures IV-2a and IV-2b show the number of detections versus ordinary clock time (horizontal axis is the time-to-detect, t_d) and clock time shifted by the time to first visit (horizontal axis is the difference between time-to-detect and first arrival time, t_d-t_1). As expected, the time-to-detect curve shows the same delays as the first arrival time curve (compare to Fig. III-12). The shifted time curve, t_d-t_1, should be more reliably predictable from the neoclassical model since any orientation delay or multi-stage search should be incorporated into the time to first visit, t_1, and will not influence the shifted time, t_d-t_1, to the same degree. In general, there are three exponents involved but for $J = S$ only two exponents enter. The problem is made simpler by the fact that for the shifted time

coordinate, the initial conditions are known exactly; if one uses shifted time, the observer is known to be examining the target of interest for zero shifted time.

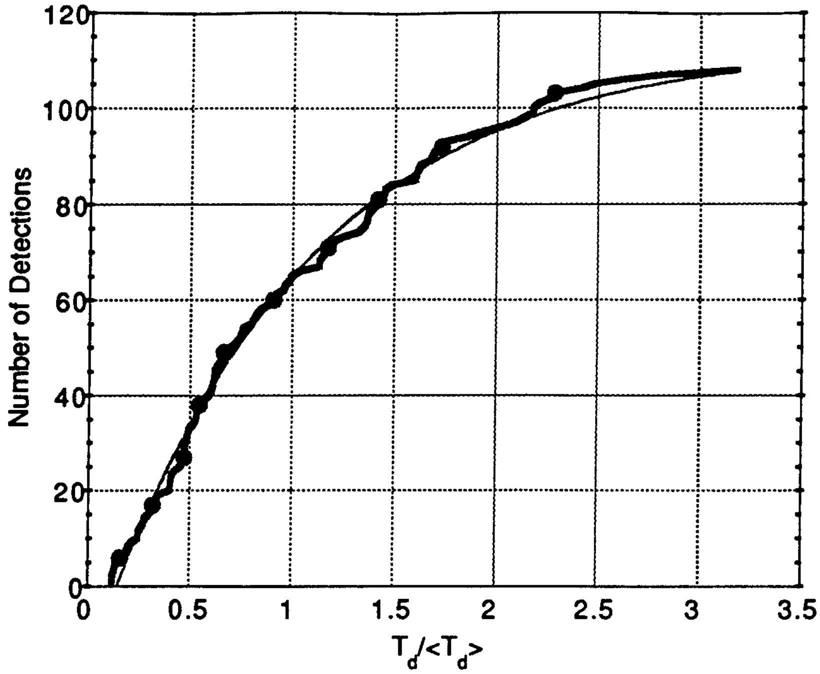

Figure IV-1a. Cumulative Detections vs. Normalized Time on Target

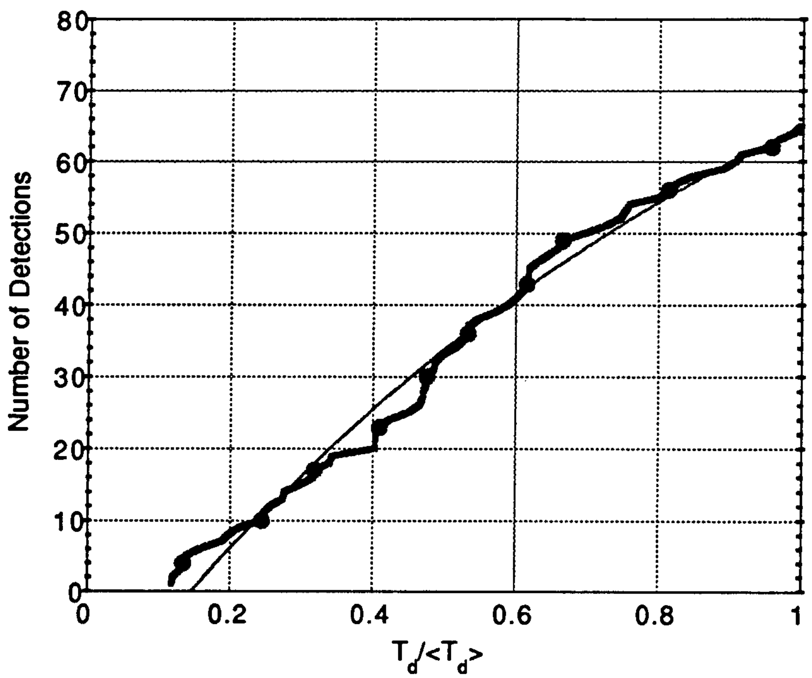

Figure IV-1b. Cumulative Detections vs. Normalized Time on Target (Detail)

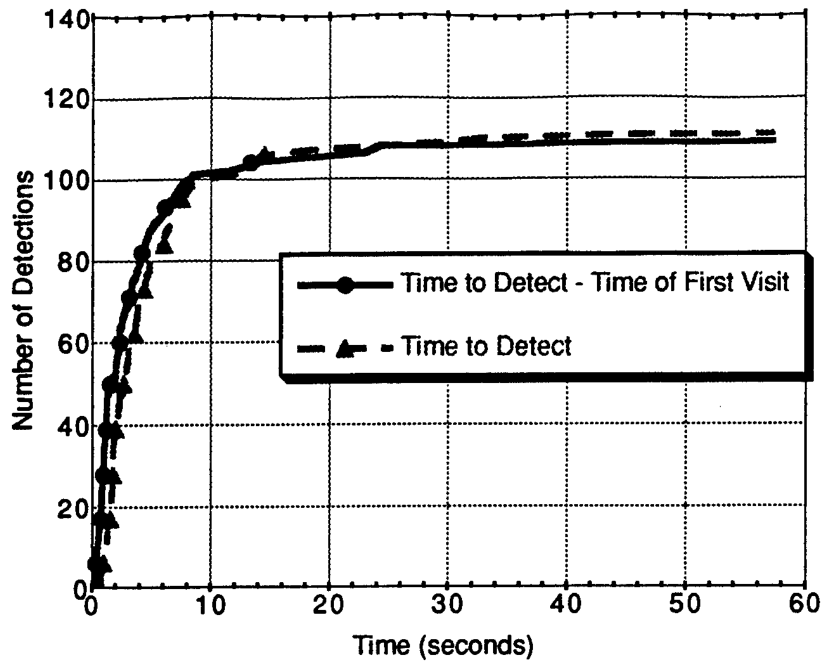

Figure IV-2a. Cumulative Detections vs. Time

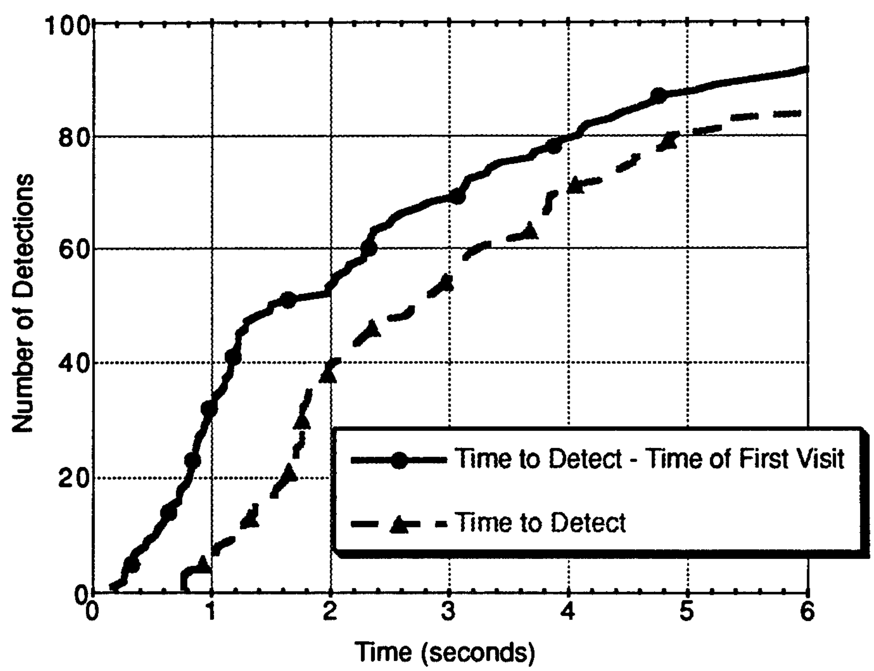

Figure IV-2b. Cumulative Detections vs. Time (Detail)

The eigenvalues and amplitudes for the $J = S$ case are:

$$\lambda_{+,-} = \frac{W + S + \alpha_0 \pm \sqrt{(W + S + \alpha_0)^2 - 4\alpha_0 S_0}}{2} \qquad \text{(IV-3a)}$$

$$e_i = \frac{\lambda_j - \alpha_0 p_0(0)}{\lambda_j - \lambda_i} \;, \qquad \text{(IV-3b)}$$

where $p_0(0)$ is the initial probability of examining the target: $p_0(0)=1$ for the shifted time case. All of the parameters needed are extractable from the data:

$$\alpha_0 = \frac{1}{<T_d>}$$

$$S_0 = \frac{1}{<T_{gap}>} \qquad \text{(IV-4)}$$

$$W + S = \frac{S_0}{p_{eq}} \quad .$$

Note the most problematic quantity is the equilibrium fraction of time spent on the target, p_{eq}, which as discussed in Section II above, cannot be extracted from the data with complete confidence. However, it should be calculable from first principles from a human vision theory and the target and background characteristics, since it should be essentially equal to the single glimpse probability of being cued to the target. The data show qualitatively the effects expected in the neoclassical approach; the number of detections should rise relatively sharply initially (during the first visit to the target) and then rise at a slower rate as the other points of interest are visited before the observers return to the target.

Figure IV-3 shows the values of the two eigenvalues as calculated from Eq. (IV-3) as a function of the P_∞ value of the targets and using the value of p_{eq} appropriate to the average detection time (compare to Eq. II-1). The values for the high P_∞ targets are well clustered.

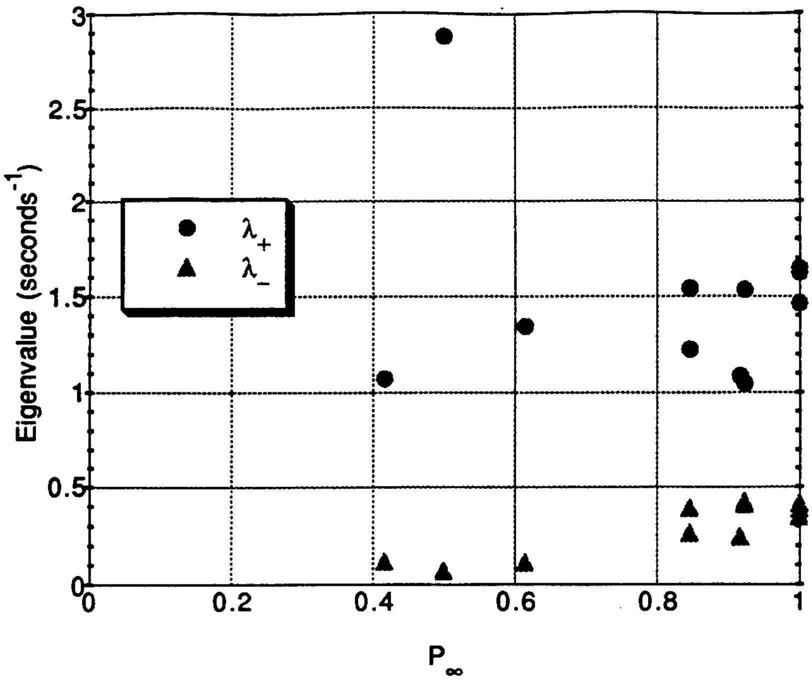

Figure IV-3. Neoclassical Eigenvalues vs. P_∞

Figures IV-4a and IV-4b show the fit to the detection target for those targets, using the neoclassical fit and average values for the exponents and amplitudes using the mean detection time [Eq. (II-1)] to estimate p_{eq}. In this graph, the eigenvalues and amplitudes were fixed from Eq. (IV-3) and Eq. (IV-4); the only adjustments permitted were for the overall amplitude and a shift in the time axis to account for the data censoring. The values of the faster and slower exponents are 1.4 and 0.36 sec^{-1}, respectively. The fit is very good except at the shortest times where there is an apparent oscillation around the fit.[1] Figures IV-5a and IV-5b show the same data fit with a value of p_{eq} taken from the ratio of visit and gap duration; in this case the exponents are significantly different, 2.1 and 0.24 sec^{-1}, respectively, but the overall quality of the fit is very similar except at the longest times. The fit is not exceptionally sensitive to the large difference in the exponents but the fit in Fig. IV-4 is somewhat better in all regions.

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1 These oscillations have been seen at short times in other experiments, notably a 1993 experiment conducted at the Human Engineering Laboratory, Aberdeen, MD [Birkmire et al. (1992)]. They have been simulated numerically in a Monte Carlo simulation by J.F. Cartier et al. (1994). With the neoclassical framework such oscillations could be represented as a *second-order* Markov process that has complex eigenvalues and hence possible oscillations.

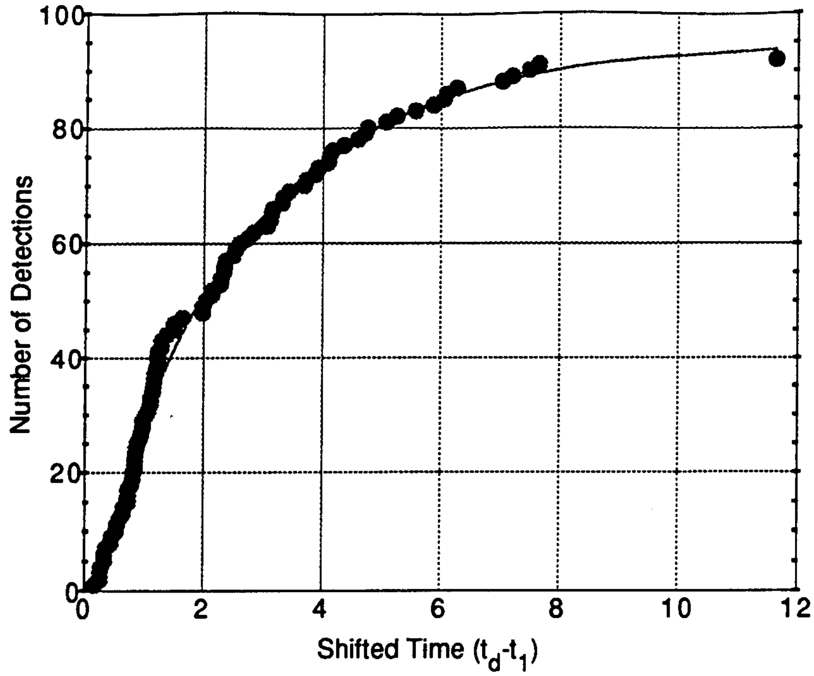

Figure IV-4a. Cumulative Detections vs. Shifted Time and Neoclassical Model Fit Using Mean Detection Time p_{eq}—Omitting Targets 1, 4, and 5

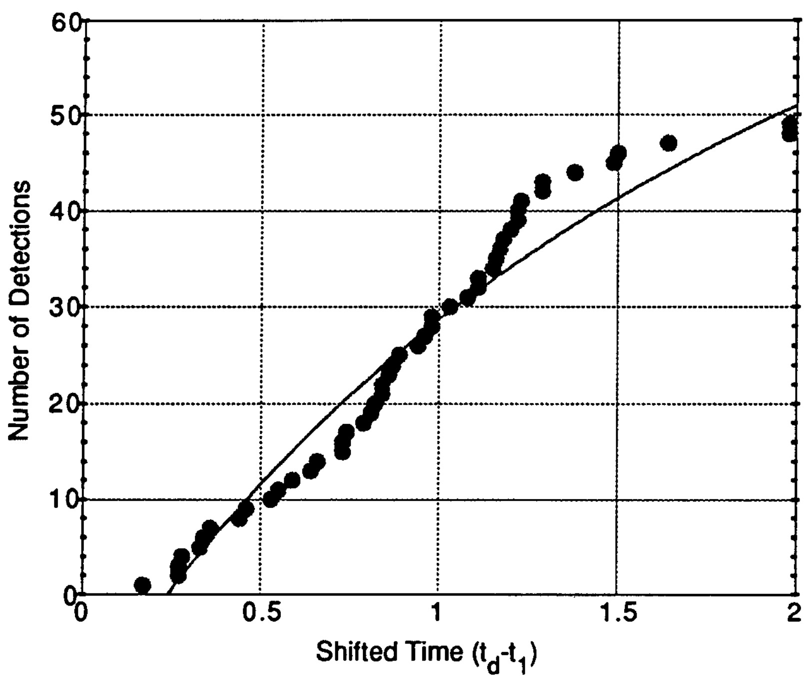

Figure IV-4b. Cumulative Detections vs. Shifted Time and Neoclassical Model Fit Using Mean Detection Time p_{eq}—Omitting Targets 1, 4, and 5 (Detail)

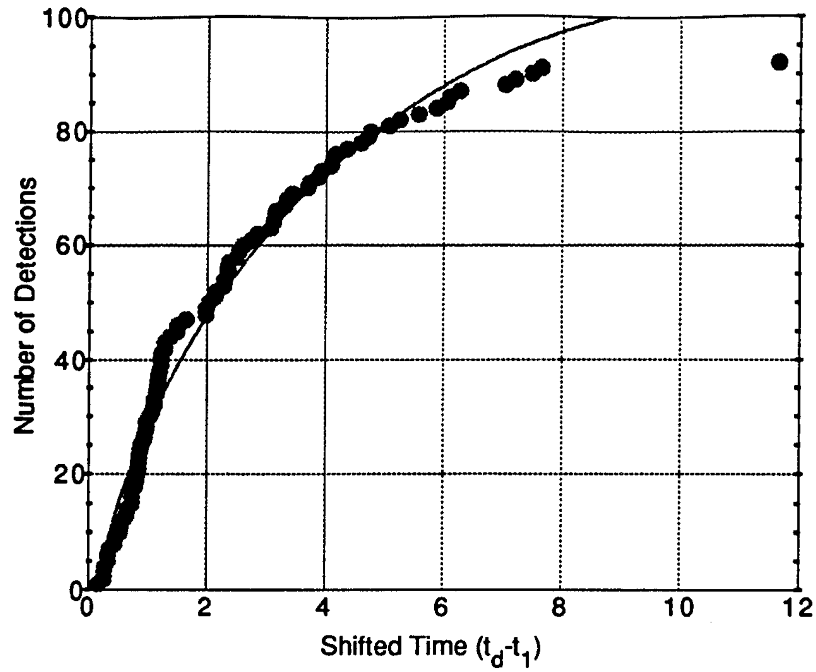

Figure IV-5a. Cumulative Detections vs. Shifted Time and Neoclassical Model Fit Using Visit Data p_{eq}—Omitting Targets 1, 4, and 5

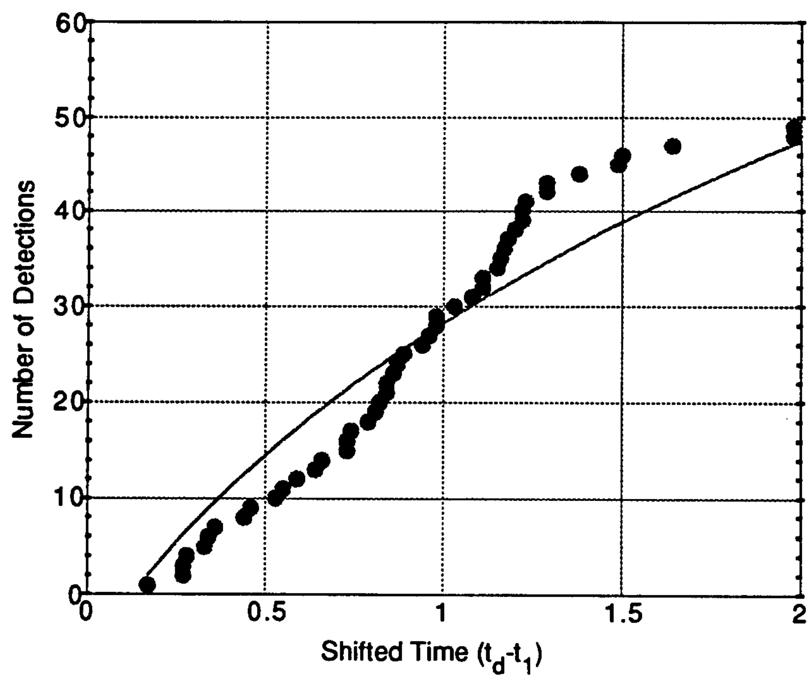

Figure IV-5b. Cumulative Detections vs. Shifted Time and Neoclassical Model Fit Using Visit Data p_{eq}—Omitting Targets 1, 4, and 5 (Detail)

This agreement with the predictions of the neoclassical model is encouraging. However, in this case, a single exponent approximation is also adequate as shown in Figs. IV-6a and IV-6b using a single eigenvalue of 0.46 sec^{-1} (chosen to match the average value of t_d-t_1). As anticipated in Section II, these targets are well described by the classical approach so, although consistent with the neoclassical model, they do not require it. Figures IV-7a and IV-7b show this directly by plotting the detection data for these targets against total detection time using an average classical time constant [Eq. (II-2)] for these targets of 3.66 seconds. The fit is again very good except at the longest times and the shortest times where the oscillation is, of course, apparent.

The conclusion is that for relatively conspicuous targets both the neoclassical model and the classical search models perform adequately. There are discrepancies that are of some interest, namely the time until the first arrival at the target, which has more structure than is anticipated in either the classical or neoclassical model as presented here, and the oscillations in the detection rate at short times after the first visit. However, for the majority of purposes the classical model provides an acceptable description.

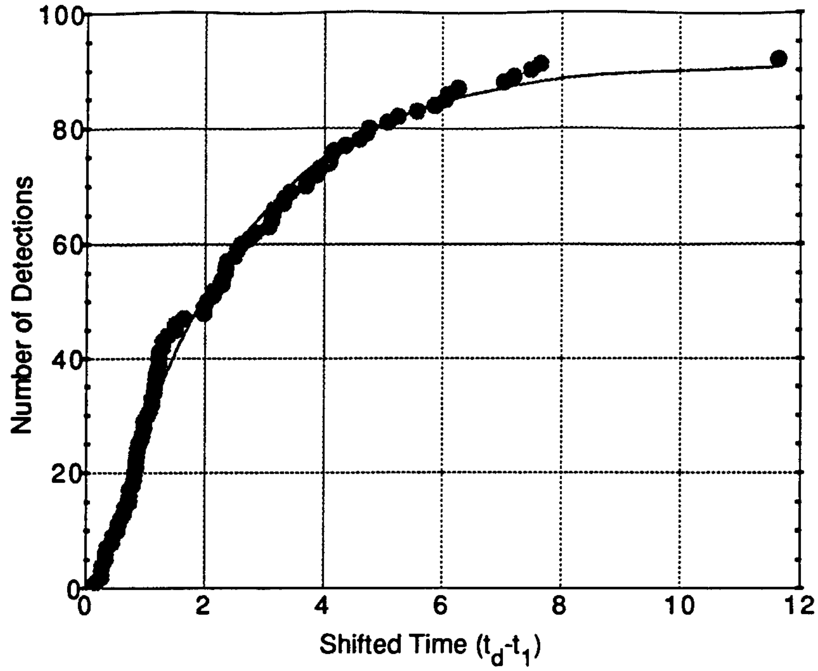

Figure IV-6a. Cumulative Detections vs. Shifted Time and Single Exponent Fit—Omitting Targets 1, 4, and 5

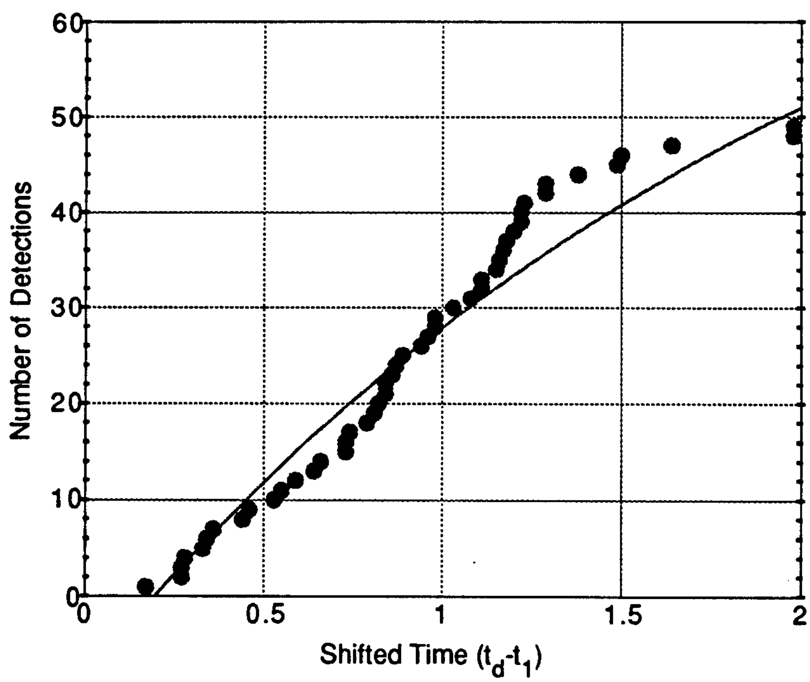

Figure IV-6b. Cumulative Detections vs. Shifted Time and Single Exponent Fit—Omitting Targets 1, 4, and 5 (Detail)

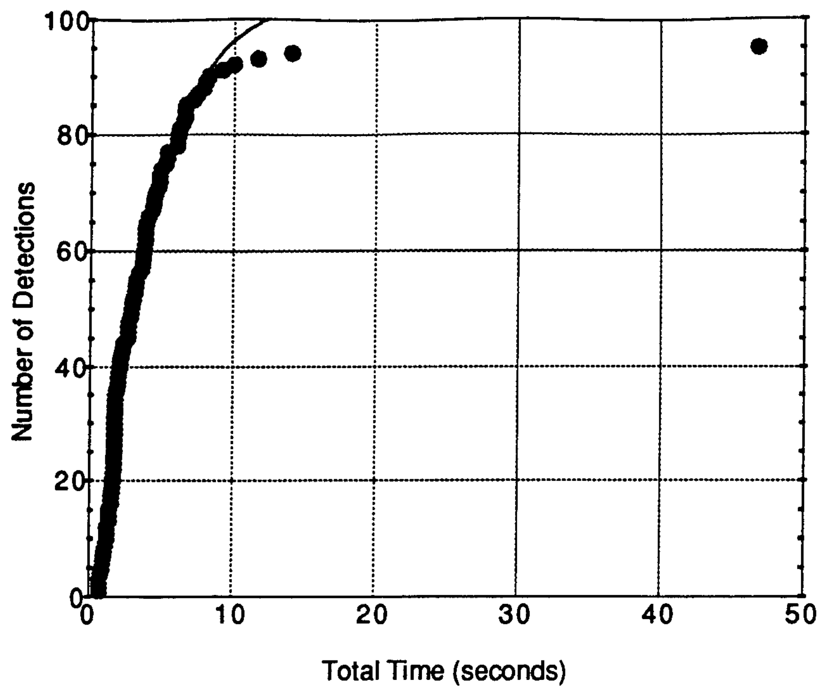

Figure IV-7a. Cumulative Detections vs. Total Time and Classical Model Fit—Omitting Targets 1, 4, and 5

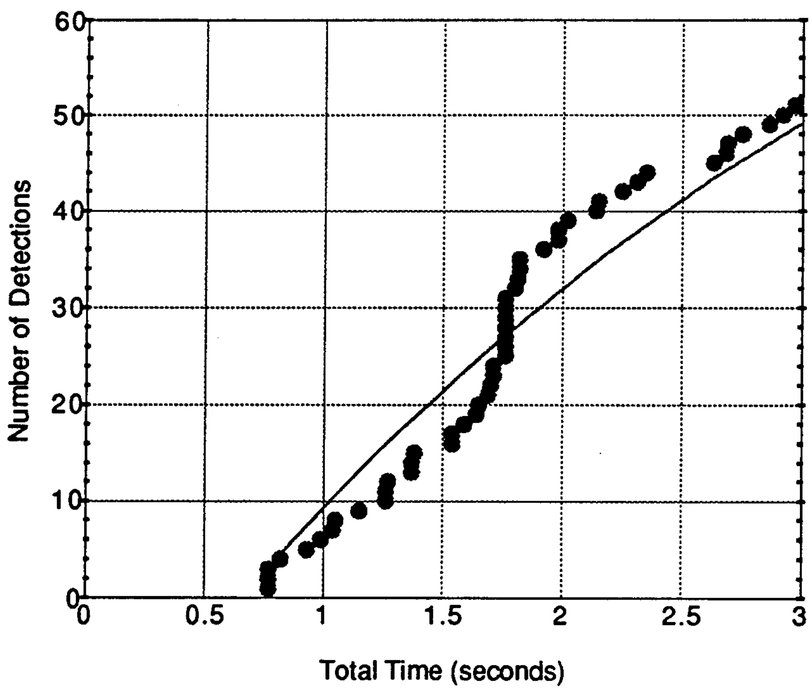

Figure IV-7b. Cumulative Detections vs. Total Time and Classical Model Fit—Omitting Targets 1, 4, and 5 (Detail)

Using targets 1, 4, and 5, which have the lower values of P_∞, is a more interesting case. Figures IV-8a and IV-8b show the detection results versus shifted time for these targets and the neoclassical fit. The exponents and amplitudes again were determined from the search and detection rate parameters (with p_{eq} taken from the mean detection time) and are not free parameters in this fit. The average fast and slow exponents for these targets are 1.77 and 0.098 sec^{-1}, respectively. The limited number of data points in this restricted data set reduces the precision of the estimates of any of the search and detection parameters. Thus the high quality of the fit is even more striking.

As anticipated, this data shows the qualitative effects predicted by the neoclassical model more strongly. The initial rise in the number of detections is sharp and after the first visit the detection rate is noticeably reduced. This is reflected in the clear change in slope illustrated in Fig. IV-8b. This data, limited though it is, provides confirmation of the neoclassical model approach. The same result is shown in Figs. IV-9a and IV-9b, which use the visit and gap duration to estimate p_{eq}; the exponents for this case are 2.0 and 0.077 sec^{-1}; the overall quality of the fit is essentially as good.

However, even for these targets, the classical model can, with suitable adjustments, provide a reasonable fit. Figures IV-10a and IV-10b show a classical model fit to the number of detections versus total time with an average classical time constant of 6.83 seconds. Two fits are shown; a simple exponential with the classical exponent and the simple exponential with a delay to accommodate the problems with the time to the first visit. The computed delay of 1.1 seconds is much too long to be a consequence of the data smoothing. The fit for both long and short times is reasonably good. Finally, Figs. IV-11a and IV-11b show a neoclassical fit to the number of detections versus total detection time. For this plot, a value of $p_0(0) = 0.06$ was taken, corresponding to 1 observer (of the 18 observer-target combinations) starting at the target. The corresponding amplitudes are 1.05 for the slow (dominant) exponent and – 0.05 for the fast exponent. The fits are excellent and superior to the classical fit; however, the amplitude for the fast exponent is so small that a single exponent fit with a value of 0.07 sec^{-1} (slower than the classical prediction from P_∞) would fit essentially as well (Figs. IV-12a and IV-12b).

The conclusion to be drawn from these targets is that the neoclassical model assumptions and framework are supported both qualitatively and quantitatively. The simplest classical model prediction of the single exponent time constant from P_∞ does not work well but, at least for the total detection time representation, a single exponent with a non-classical value of the time constant is a good representation.

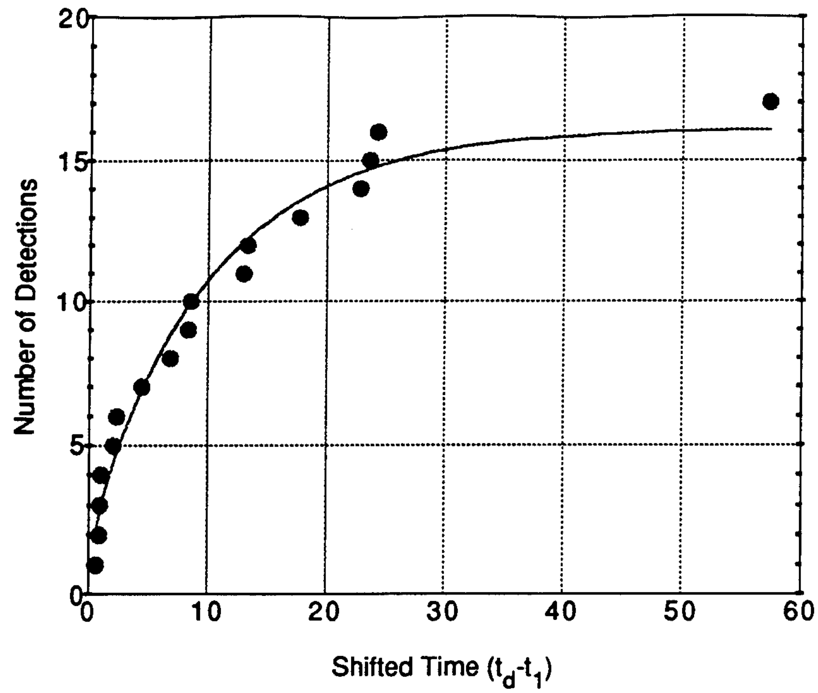

Figure IV-8a. Cumulative Detections vs. Shifted Time and Neoclassical Model Fit Using Mean Detection Time p_{eq}—Targets 1, 4, 5

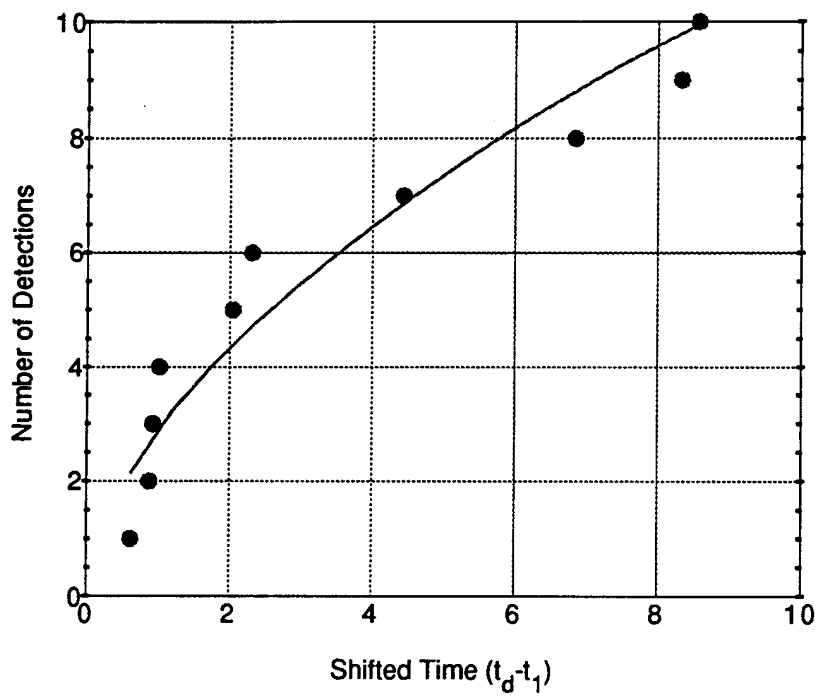

Figure IV-8b. Cumulative Detections vs. Shifted Time and Neoclassical Model Fit Using Mean Detection Time p_{eq}—Targets 1, 4, 5 (Detail)

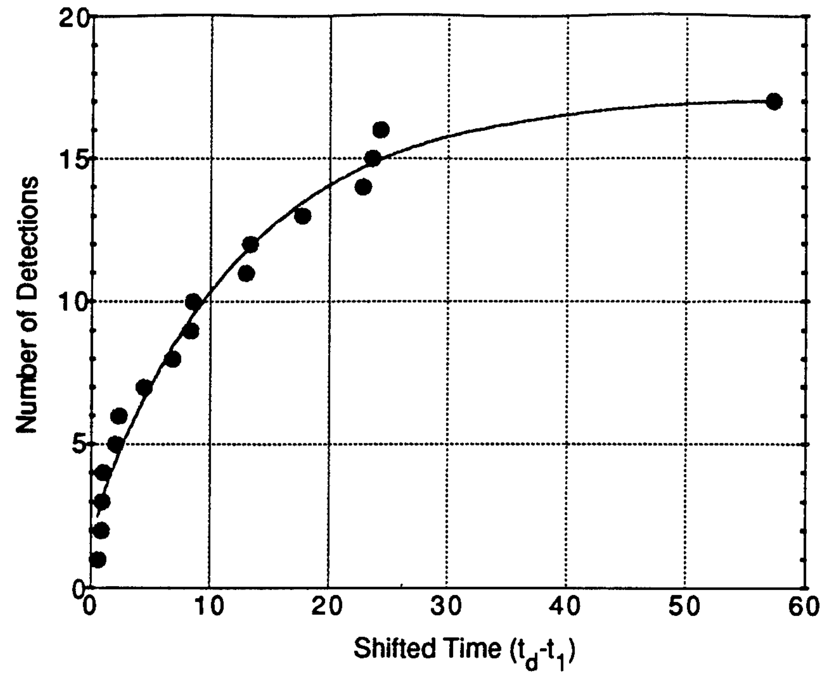

Figure IV-9a. Cumulative Detections vs. Shifted Time and Neoclassical Model Fit Using Visit Time p_{eq}—Targets 1, 4, 5

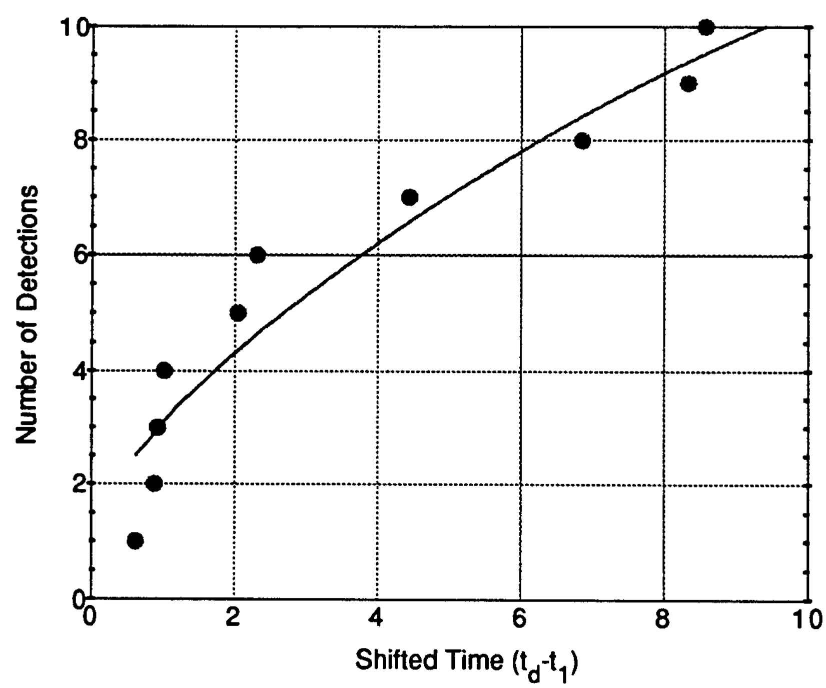

Figure IV-9b. Cumulative Detections vs. Shifted Time and Neoclassical Model Fit Using Visit Time p_{eq}—Targets 1, 4, 5 (Detail)

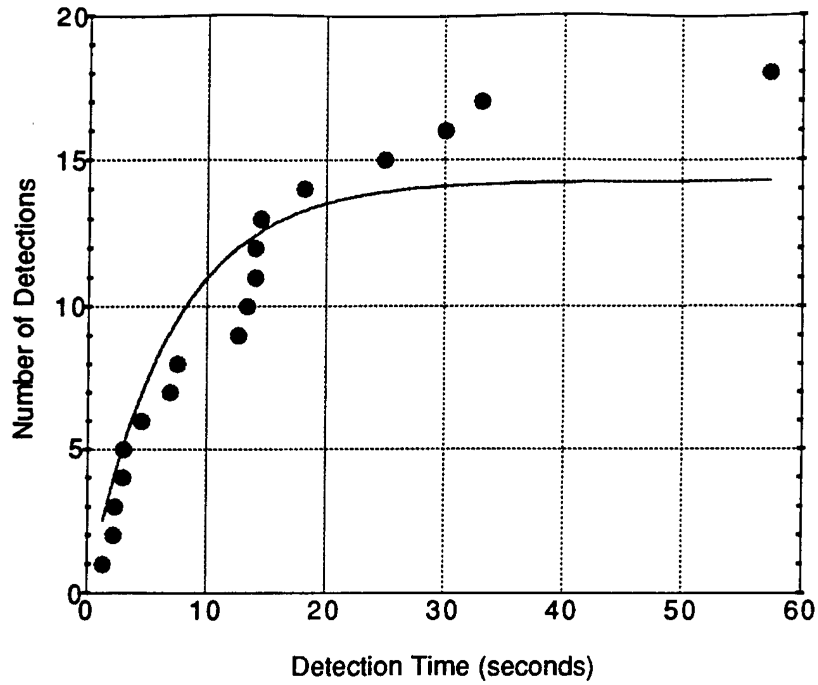

Figure IV-10a. Detection vs. Total Time and Classical Model Fit—Targets 1, 4, 5

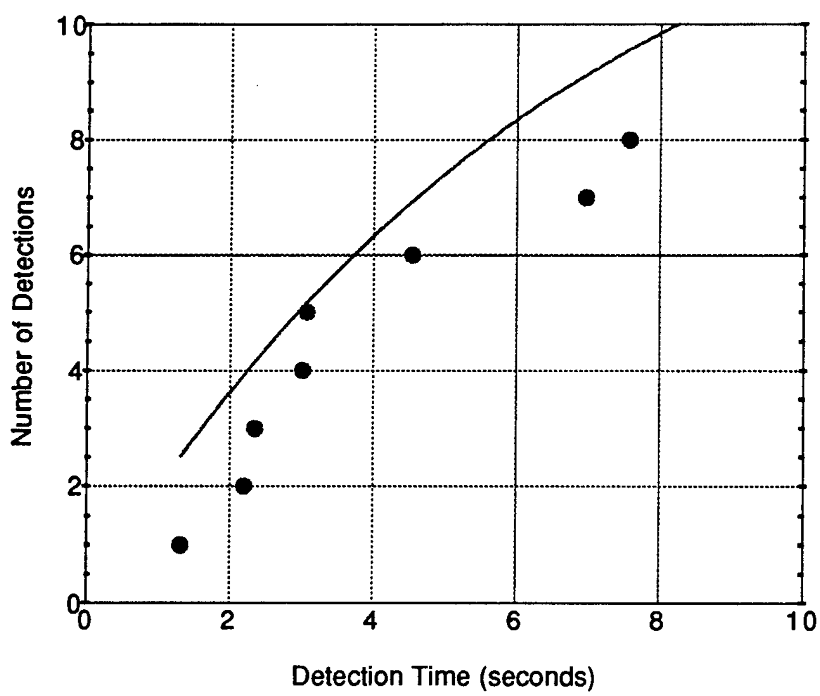

Figure IV-10b. Detection vs. Total Time and Classical Model Fit—Targets 1, 4, 5 (Detail)

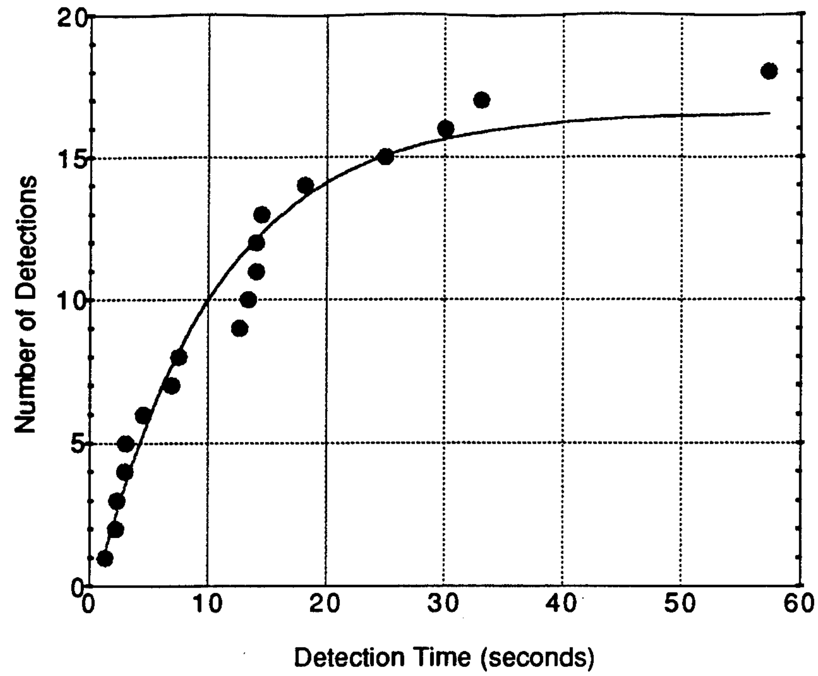

Figure IV-11a. Detection vs. Total Time and Neoclassical Model Fit—Targets 1, 4, 5

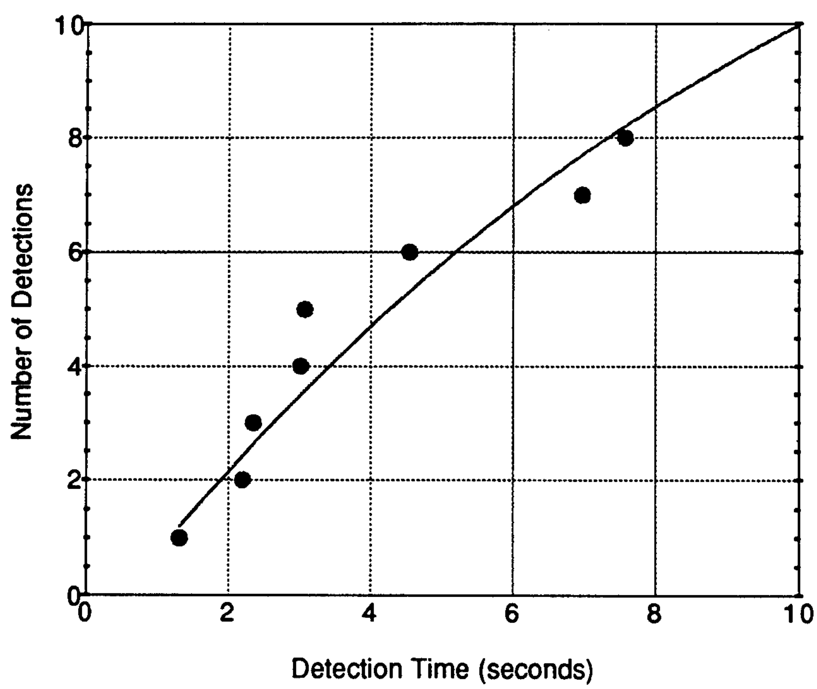

Figure IV-11b. Detection vs. Total Time and Neoclassical Model Fit—Targets 1, 4, 5 (Detail)

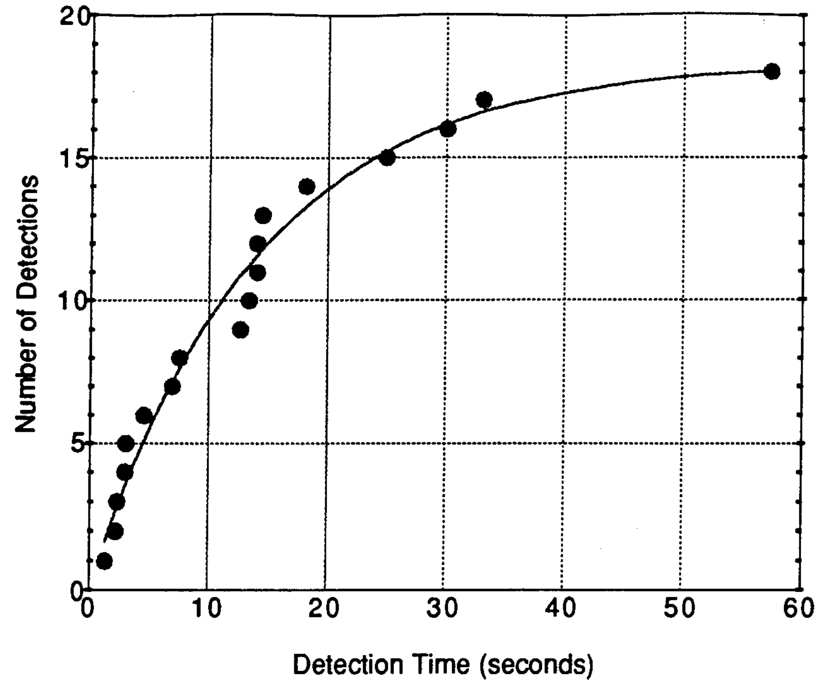

Figure IV-12a. Detection vs. Total Time and Single Exponent Fit—Targets 1, 4, 5

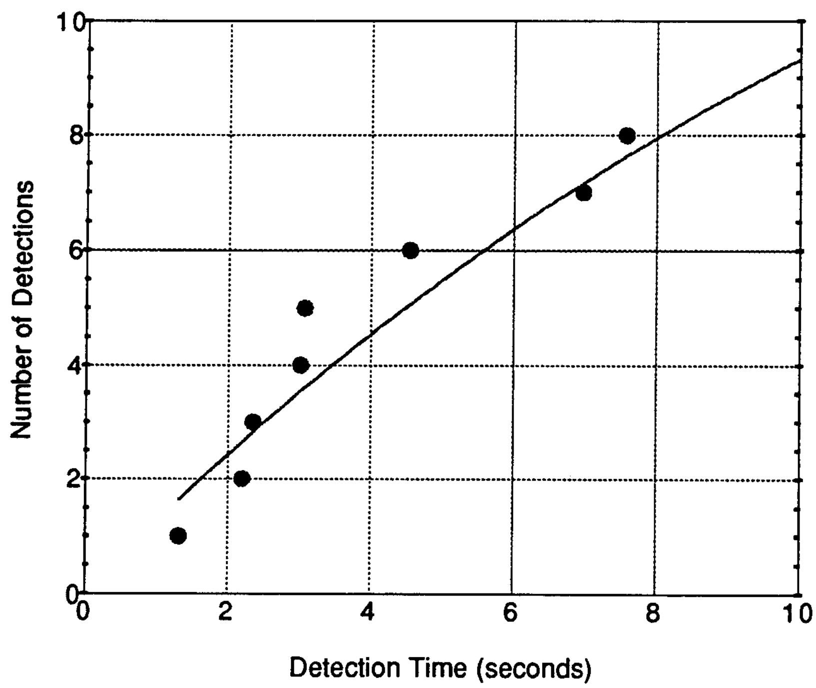

Figure IV-12b. Detection vs. Total Time and Single Exponent Fit—Targets 1, 4, 5 (Detail)

V. CONCLUSIONS

The eye-tracking data from the NVL 4B perception experiment has provided convincing evidence to support the underlying assumptions of the neoclassical framework for search and detection models. Ideally, this study would have been accompanied by predictions of the search model parameters from the computational vision models under development. In principle, the search and eye-tracker data could itself be used to compute the search parameters. However, the limited number of observers makes it difficult to estimate the parameters sufficiently accurately to perform a parametric test on correlation of the parameters with other target and background characterizations. This is especially true for the objects with lower value of P_∞ since the number of detections is proportionally reduced. In the absence of independent predictions of the parameters, only consistency with the neoclassical model could be obtained.

We have developed several methods for separating "wandering" and "examination" states using both velocity filters (the observer's eye position should be changing slowly during an examination visit) and simple position (examinations occur when in a box drawn around the target) and have found reasonable agreement. Methods of filtering the eye-tracker data to avoid false examinations and false examination ends have been developed. The conclusions that can be confirmed by the 4B data are enumerated as follows:

1. Visual examination of the patterns of eye motions confirms the "random" nature of the search assumed in the neoclassical framework. The observers move rapidly from point to point in the image without any evidence of a systematic search pattern.
2. The measured eye positions can be divided relatively easily into wandering and examining states as assumed in the neoclassical framework. There are clear points of interest that are heavily examined and a diffuse field of other locations captured by the eye-tracker spread over the entire image.
3. There are multiple visits to the target both before and after the observer makes a detection decision (see Figs. III-1, III-2, and III-3).
4. A detection model that is exponential in the time-on-target is appropriate. The targets were relatively easy to detect when the observer has been cued to the target: 65 percent of the targets were detected on the first visit (see Fig. III-2 and Fig. IV-1).

5. The process of examining the target is consistent with a Markov model of the search. For any first order Markov process, the durations of the visits to the target should have a distribution described by a single exponential function (cf. Figs. III-3, III-5, III-6, III-9, and III-11).

The separations between visits are a probe of the details of the Markov process. For the full neoclassical model, the gap distribution should be described as the sum of two exponentials. For the special case of $J = S$, the distribution reduces to a single exponential. It was anticipated that the numerical difference between these cases might be small:

6. The $J = S$ single exponential case is a reasonable fit for the visit separation data in this experiment although there is weak evidence for a second exponent (see Figs. III-15, III-16, and III-17). As shown in Appendix A, it is difficult to separate these cases with the currently available data.

The probability of detection is, of course, the prediction of primary interest in any search and detection model. The neoclassical framework permits up to three exponents in the description of detection, but it was anticipated that the numerical difference between the full three-exponent result that follows from the general framework and single exponent approximations might be small. This was indeed the case—single exponent fits with a free exponent do a reasonable job of predicting the detection behavior, either when plotted against total clock time or against shifted time (the time to detect minus the time of first arrival). The neoclassical fits to the data use the exponents and amplitudes calculated from the search model parameters as extracted from the data (visit lengths and gap durations) and the time-on-target to detect. The actual clock time to detect is therefore predicted from these parameters

7. The neoclassical model predictions are consistent with the number of detections versus both total clock time and shifted time (see Figs. IV-2, IV-4, and IV-5).

8. Qualitative features of the neoclassical model are exhibited. For example, the number of detections versus shifted time shows an apparently large detection rate initially during the first visit to the target and a somewhat slower subsequent detection rate (see Fig. IV-5). In this experiment the effect was not dramatic enough to exclude single exponent fits (see Figs. IV-6 and -7).

All of the above results support the neoclassical model framework and its assumptions. From a practical point of view they mean that the search and detection can be adequately described by a limiting case of the neoclassical model that is completely determined by three parameters:

(1) The mean time-on-target required for detection. This is the average amount of time spent by the observer examining the target directly required to declare a point of interest to be a target. This is a measure of the difficulty in determining the character of a target and may be longer for deceptive targets.

(2) The fraction of time spent on the target. The observer's time is divided between the target of interest, other distracting target candidates, and general wandering in the field of view. The overall fraction of time spent on the target is a measure of the overall attractiveness of the target and its surroundings.

These two parameters are sufficient to provide a good description of the distribution of target detection times from the moment of first encounter with the target.

(3) The average length of a visit to a target. This time scale, in conjunction with the fraction of time spent on the target, determines the lengths of visits and the separations between visits. For the limiting case supported by the data analysis, it also provides the mean time to the first encounter with the target.

The remaining parameters of the full neoclassical model cannot be reliably determined by examination of the detection data in the 4B experiment and are essentially irrelevant for single target detection (they may be more relevant for multi-target correlation).

There are necessarily some caveats:

1. Preliminary analysis indicates that the time to the first visit is not well described by either the $J = S$ or the $J \neq S$ variants of the neoclassical search model or any version of the classical model (see Fig. III-12).

Several processes are involved: First, there is an initial delay in the process that may be due to the orientation of the observer. Second, the observers then appear to search very quickly; this may be due to the two-stage search process proposed by many (cursory search for the obvious targets, followed by more leisurely search). For targets that are difficult to locate, the time to first visit may be as relevant as the time to detection. Although the details of the first visit time distribution require further understanding, the mean time to the first visit is consistent with the neoclassical prediction.

2. The overall fit to the data with a single exponent, while not as good as the neoclassical two-exponent fits, is acceptable. For targets with relatively large values of P_∞ even the value of the exponent is well represented by the classical approximation $\tau = 3.4/P_\infty$. For targets with lower P_∞, a single exponent fit is appropriate but requires a non-classical value of the time constant (see Figs. IV-6 and IV-7).

3. The duration of the detection visit is longer than the typical pre-detection visit and has a clear distinct distribution, the most obvious explanation being extra

cognitive processing upon making the decision. This may have some consequences for multi-target search (see Fig. III-5).

4. The pre-detection and post-detection distributions of visit durations and separations between visits appear to differ significantly, see Figs. III-4 and III-6). This implies some learning in the search process so that a memory-less Markov search process only approximates a more complex behavior. This is of importance for multiple-target searches but does not affect the single target problem.

There are a number of issues that require further study within the 4B experiment ~~and~~ which may suggest the need for further experimental and theoretical efforts:

1. The conclusion that $J = S$ was made on the basis of examining the visit and detection data rather than an identification of each transition. Further analysis may be able to test the equality directly. (Appendix A discusses whether or not one can, in principle, test for $J = S$ without such direct tests.)
2. The parameters used in the description of the data were extracted from the data rather than being predicted *a priori* from a target signature and vision model. Further analysis may be able to correlate these parameters with observable features of the image, if not from a computational vision model.
3. Only the most salient point of interest in each image was explicitly considered in the current analysis. Further supporting information about the nature of the search can be obtained by extending the analysis to all the points of interest.
4. The deviations from the strict classical prediction of overall time-to-detect in this experiment lay primarily in the low P_∞ targets. Unfortunately, these targets are the most difficult to study since fewer observers declared them as targets. However, a more detailed analysis may provide further insight into the search and detection parameters of these targets.[1]
5. The targets used were relatively easy to detect. For most targets, the mean number of visits required to detect was about 1.5. More difficult targets would provide a clearer test of the neoclassical model.
6. Since the neoclassical model fits depend entirely on just three parameters, the final recommendation is that a concerted effort be made to understand these parameters and their dependence on target signatures and backgrounds in greater detail.

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1 For example, one of the mechanisms for producing a value of $P_\infty < 1$ discussed in Nicoll (1994) is a quitting mechanism. Were the observers quitting before spending sufficient time on these targets to detect because they were distracted by other points of interest?

Although, as in any experiment with human observers, the cogency of these conclusions may be limited by the size of the data base, the overall conclusion is that the foundations of the neoclassical search model are validated by this experiment.

GLOSSARY

ARPA	Advanced Research Projects Agency
NVESD	U.S. Army Night Vision and Electronic Sensors Directorate
NVL	Night Vision Laboratory
TAMIP	U.S. Army Target Acquisition Model Improvement Program
POI	point of interest

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APPENDIX

DETERMINABILITY OF $J = S$

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DETERMINABILITY OF $J = S$

In the body of this paper, it was shown that the simpler limit of the neoclassical model for which all the values $J_i = S_i$ is compatible with the data analyzed. This limit corresponds to no distinction being made between the probability of cueing to a point of interest from the wandering state or from the examination state of a different point of interest. The $J = S$ limit is simpler for data analysis because it implies that only one exponent is needed to describe the time to first arrival at a target and only two exponents are needed for the full probability of detection. The data analyzed for the time to detect given first arrival clearly did not show the need for three exponents and was in fact adequately represented with one!

On the other hand, it seems *a priori* unlikely that $J = S$, since this would imply that the cognitive state of the observer was essentially identical in wandering and examining states. In addition, the simplest method of separating wandering versus examining states from the eye-tracker data is to impose a velocity threshold on the eye movements: when the eye is moving slowly, it is examining with more rapid saccadic movements between examinations. If this procedure is used, it virtually rules out any "J" transitions: each examining state is ended by a rapid movement to another examining state with the intermediate time classified as wandering. In this case, $J_i = 0$.[1]

In this Appendix we show that, given constraints on the data from overall average quantities, it is impossible in practical terms to distinguish between the $J = S$ and $J = 0$ cases. It is convenient to use some of the measured average quantities. Define

---

1 If one wishes to use the same velocity-based algorithm for identifying examination states but use a non-zero value of J, the eye-tracker data recording eye-positions between examinations would have to be divided into "true" wandering positions and eye-positions recorded during a jump between examinations. In some cases, it seems clear that a sequence of recorded positions is either a wander in the neoclassical sense (the path is curved and only moderately fast with both faster and slower portions) or a jump (rectilinear, high-speed path with essentially constant velocity). However, we have not been able to construct a satisfactory set of criteria that can automate this classification.

$$R = W + S = g_1(W + J) \quad \text{(A-1a)}$$

$$\frac{(S_0 - J_0)W}{(W + S)(W + J)} = g_2 p_{eq} \quad \text{(A-1b)}$$

$$W = g_3(W + S) \quad , \quad \text{(A-1c)}$$

where p_{eq} is the equilibrium fraction of the time spent examining the point of interest (cf. Eq. III-5b). Note that $g_3 = p_{wander}$, the fraction of time spent wandering rather than examining. The value of $W + J$ provides the basic time scale of the search and is determined by the mean length of a visit, T_{visit}, p_{eq} and g_2:

$$W + J = \frac{1}{T_{visit}(1 - p_{eq}(1 - g_2))} \quad . \quad \text{(A-2)}$$

The dimensionless factors g_1, g_2, and g_3, combined with the easily measured mean time on target to detect, $T_d = 1/\alpha$, and equilibrium probability, p_{eq}, and the boundary conditions define all the needed parameters of the neoclassical model. For example, the mean time to the first visit [Eq. (III-5a)] can be rewritten as:

$$< t_1 >= \frac{T_{visit}(1 - p_{eq}(1 - g_2))}{p_{eq}}[1 - w(0)p_{eq}\frac{g_2}{g_1 g_3}] \quad . \quad \text{(A-3)}$$

Individual values of neoclassical model parameters can be expressed in these terms. For example, the value of the jumping rate to the target, J_0, is given by:

$$J_0 = \frac{p_{eq}(1 - g_2)}{T_{visit}(1 - p_{eq}(1 - g_2))} \quad . \quad \text{(A-4a)}$$

Note that it depends only on g_2. The transition rate from the wandering state, S_0, depends on g_2 and g_3 and is given by:

$$S_0 = \frac{p_{eq}(1 - g_2 + \frac{g_2}{g_3})}{T_{visit}(1 - p_{eq}(1 - g_2))} \quad . \quad \text{(A-4b)}$$

The eigenvalue equation is written as:

$$\lambda'(\lambda' - g_1)(\lambda' - (1 + \alpha')) - \alpha' p_{eq}(g_1 - (1 - g_2)\lambda') = 0 \quad \text{(A-5a)}$$

where

$$\lambda' = \frac{\lambda}{W+J} \quad ; \quad \alpha' = \frac{\alpha}{W+J} \quad . \tag{A-5b}$$

As shown by Eqs. (A-2) and (A-5), the eigenvalues do not depend on g_3, which only enters in terms dependent on the boundary conditions, such as the precise coefficients of the exponents and the time to the first visit [cf. Eq. (A-3)].

The extreme cases for $J = 0$ and $J_i = S_i$ are easily described in terms of the g_1 and g_2 as illustrated in Table A-1. The value of g_3 is always given by p_{wander}. Note that in the case of $J_i = S_i$, all results are independent of the value of g_3.

Table A-1. Values for g_1, g_2, and g_3

Parameter/Case	$J = 0$	$J_i = S_i$
g_1	$1/g_3$	1
g_2	1	0
g_3	p_{wander}	p_{wander}

Using these parameterizations and holding α, T_{visit}, and p_{eq} fixed, we may now investigate the differences between the two extreme neoclassical cases: $J = 0$ and $J_i = S_i$. The values $\alpha = 0.5\ sec^{-1}$, $T_{visit} = 2.5$ seconds, $p_{eq} = 0.50$ were chosen to be typical of the data found in the IV-B experiment. As in the main body of the paper, it is useful to separate the predictions into the probability of detection measured in terms of the time to detect since the first arrival at the target (P_d versus shifted time), the distribution of visit separations and the distribution of times until first arrival. Figure A-1 shows the probability of detection versus shifted time for 4 cases:

1. Single exponent model. This uses a single exponent with a time constant:

$$\tau_{single} = \frac{1}{\alpha p_{eq}} \quad . \tag{A-6}$$

   This provides the correct average time to detect from first arrival.

2. The $J = S$ case. This and the other neoclassical results rise faster than the single exponent case (because the observer is known to start at the target) and then crosses the single exponent result (in order to have the same average time). This curve uses two exponents.

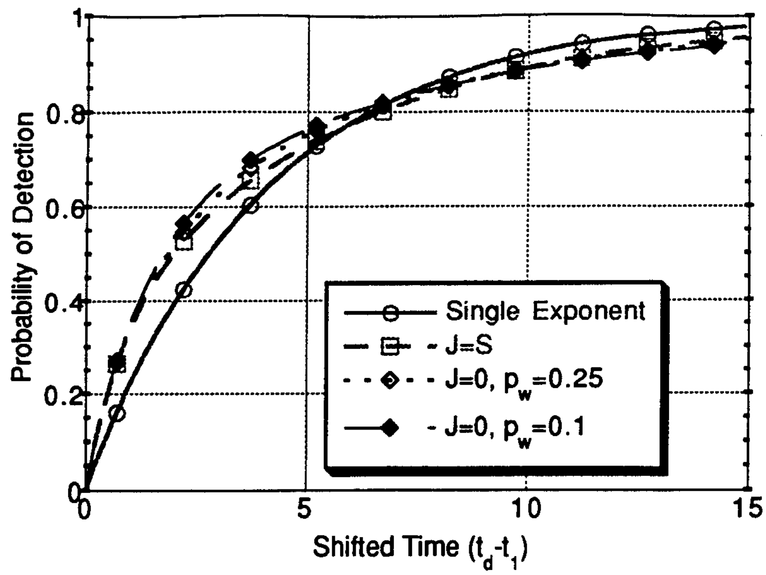

Figure A-1. Probability of Detection vs. Shifted Time

3. The $J = 0$ case with $p_{wander} = g_3 = 0.25$. Since the observer spends half his time on the target, this divides the remaining time equally between wandering and the other points of interest. This curve uses three exponents.

4. The $J = 0$ case with $p_{wander} = g_3 = 0.1$. In this case, the observer spends only 10 percent of his time wandering, and 40 percent on the other points of interest. This curve uses three exponents.

The important point to notice is that all three of the neoclassical results are essentially indistinguishable and that they differ only slightly from the single exponent result.

The next thing one could study is the gap between visits to the target. Figure A-1 shows three cases:

1. The $J = S$ case. This curve uses one exponent corresponding to the time constant.

$$T_{gap} = T_{visit} \frac{1 - p_{eq}}{p_{eq}} \quad . \tag{A-7}$$

2. The $J = 0$ case with $p_{wander} = g_3 = 0.25$. This curve uses two exponents.

3. The $J = 0$ case with $p_{wander} = g_3 = 0.1$. This curve uses two exponents.

Note the somewhat counter-intuitive result that the $J = 0$ cases rise initially faster than the $J = S$ case. For $J = 0$, the observer may be "trapped" by other points of interest;

since a transition directly from another point of interest back to the target is forbidden, the path between visits generally consists of more steps than for $J = S$. However, since the average time for a gap must be given by (A-7) for any choice of the parameters, g_1, g_2, and g_3, the initial rates for return (which is S_0 for all these cases but S_0 is a function of g_2 and g_3, as given in Fig. A-4b) must actually be greater for the $J = 0$ cases than for $J = S$. Similarly, the rate of return must be greater for $g_3 = 0.1$ than for $g_3 = 0.25$ but the curves are nearly indistinguishable. An examination of Fig. A-2 shows that there is some chance of distinguishing between these cases but a larger data base will be required. Compare with Fig. III-15b, which shows a trend similar to Fig. A-2.

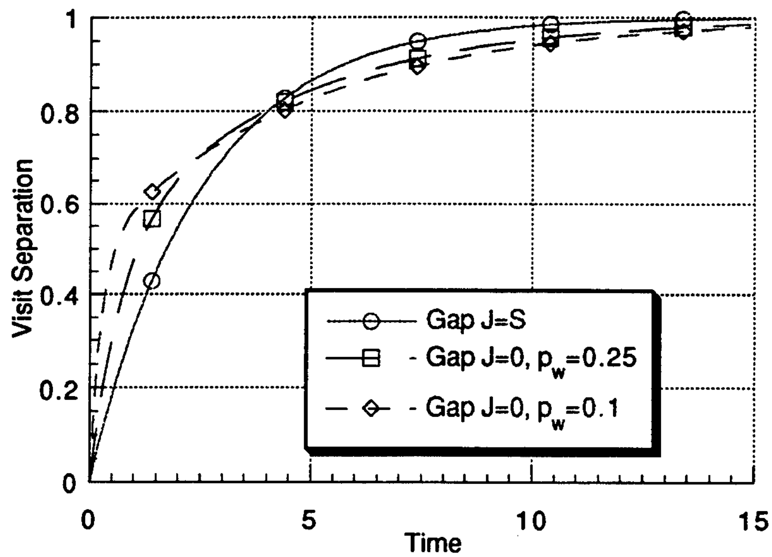

Figure A-2. Cumulative Distribution of Time Between Visits

The largest potential difference between the $J = 0$ and $J = S$ cases is the time until the first visit. Figure A-3 shows the case of observers known to be fixated on a distracter at t = 0. The two $J = 0$ cases are indistinguishable; as shown by Eq. (A-3), the mean time is independent of g_3 for $w(0) = 0$; the curves are quadratic at the origin but the range of time is so short that this is essentially irrelevant. Although the time for first arrival appears to provide some discrimination, the actual data show that additional effects are involved (see Fig. III-12), vitiating this approach.

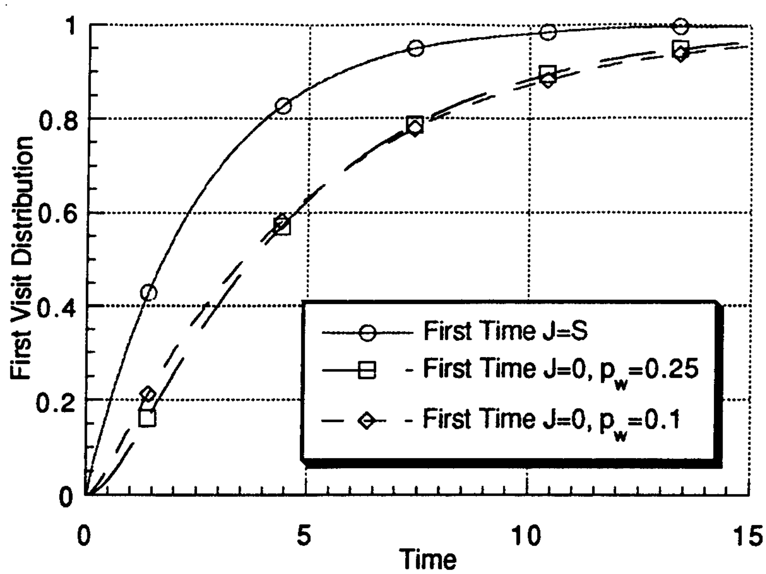

Figure A-3. Cumulative Distribution of Time Before the First Visit

The overall conclusion is that although the data given in the IV-B experiment can be analyzed in terms of the $J = S$ limiting case (with some indications in the visit separation that $J \neq S$) this does not exclude other interpretations of the data. Either a considerably more extensive database must be used to extract the more subtle effects in the data or the eye-tracker data must be analyzed to determine the values of J, S, W, J_0, and S_0 directly rather than deducing them from the visit and detection data.

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12a. DISTRIBUTION/AVAILABILITY STATEMENT

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13. ABSTRACT *(Maximum 180 words)*

The authors propose a mathematical framework for describing search and detection processes called the neoclassical model. The model uses a Markov description of search and detection and provides a method for incorporating recently developed target and clutter descriptions into the model. Based on experiments conducted by the Night Vision Laboratory, the test included eye-trackers to monitor observers' eye positions. Test data showed that: (1) measured eye locations show examination of localized points of interest and more diffuse wandering; (2) multiple visits to the target occur both before and after detection; (3) the target examination process is consistent with a Markov description; (4) a detection model exponential in the time-on-target is supported; and (5) the overall detection probability is consistent with a specialization of the neoclassical model from a three-exponent to a two-exponent form. Three parameters determine the limiting case of the neoclassical model: the mean time-on-target to detect (meaning the time actually fixated on the target before detection); the mean fraction of the total search time spent on a particular target; the mean length of a visit to a target. It is recommended that future work focus on the prediction of these quantities.

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